Methods of System Identification, Parameter Estimation and Optimisation Applied to Problems of Modelling and Control in Engineering and Physiology

A Thesis submitted for the Degree of Doctor of Science in Engineering (DSc (Eng)) at the University of Glasgow in May 2009.

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Abstract

Mathematical and computer-based models provide the foundation of most methods of engineering design. They are recognised as being especially important in the development of integrated dynamic systems, such as “control-configured” aircraft or in complex robotics applications. These models usually involve combinations of linear or nonlinear ordinary differential equations or difference equations, partial differential equations and algebraic equations. In some cases models may be based on differential algebraic equations. Dynamic models are also important in many other fields of research, including physiology where the highly integrated nature of biological control systems is starting to be more fully understood.

Although many models may be developed using physical, chemical, or biological principles in the initial stages, the use of experimentation is important for checking the significance of underlying assumptions or simplifications and also for estimating appropriate sets of parameters. This experimental approach to modelling is also of central importance in establishing the suitability, or otherwise, of a given model for an intended application – the so-called “model validation” problem.

System identification, which is the broad term used to describe the processes of experimental modelling, is generally considered to be a mature field and classical methods of identification involve linear discrete-time models within a stochastic framework. The aspects of the research described in this thesis that relate to applications of identification, parameter estimation and optimisation techniques for model development and model validation mainly involve nonlinear continuous time models Experimentally-based models of this kind have been used very successfully in the course of the research described in this thesis very in two areas of physiological research and in a number of different engineering applications. In terms of optimisation problems, the design, experimental tuning and performance evaluation of nonlinear control systems has much in common with the use of optimisation techniques within the model development process and it is therefore helpful to consider these two areas together.

The work described in the thesis is strongly applications oriented. Many similarities have been found in applying modelling and control techniques to problems arising in fields that appear very different. For example, the areas of neurophysiology, respiratory gas exchange processes, electro-optic sensor systems, helicopter flight-control, hydro-electric power generation and surface ship or underwater vehicles appear to have little in common. However, closer examination shows that they have many similarities in terms of the types of problem that are presented, both in modelling and in system design. In addition to nonlinear behaviour; most models of these systems involve significant uncertainties or require important simplifications if the model is to be used in a real-time application such as automatic control.

One recurring theme, that is important both in the modelling work described and for control applications, is the additional insight that can be gained through the dual use of time-domain and frequency-domain information. One example of this is the importance of coherence information in establishing the existence of linear or

nonlinear relationships between variables and this has proved to be valuable in the experimental investigation of neuromuscular systems and in the identification of helicopter models from flight test data. Frequency-domain techniques have also proved useful for the reduction of high-order multi-input multi-output models.

Another important theme that has appeared both within the modelling applications and in research on nonlinear control system design methods, relates to the problems of optimisation in cases where the associated response surface has many local optima. Finding the global optimum in practical applications presents major difficulties and much emphasis has been placed on evolutionary methods of optimisation (both genetic algorithms and genetic programming) in providing usable methods for optimisation in design and in complex nonlinear modelling applications that do not involve real-time problems.

Another topic, considered both in the context of system modelling and control, is parameter sensitivity analysis and it has been found that insight gained from sensitivity information can be of value not only in the development of system models (e.g. through investigation of model robustness and the design of appropriate test inputs), but also in feedback system design and in controller tuning. A technique has been developed based on sensitivity analysis for the semi-automatic tuning of cascade and feedback controllers for multi-input multi-output feedback control systems. This tuning technique has been applied successfully to several problems.

Inverse systems also receive significant attention in the thesis. These systems have provided a basis for theoretical research in the control systems field over the past two decades and some significant applications have been reported, despite the inherent difficulties in the mathematical methods needed for the nonlinear case. Inverse simulation methods, developed initially by others for use in handling-qualities studies for fixed-wing aircraft and helicopters, are shown in the thesis to provide some important potential benefits in control applications compared with classical methods of inversion. New developments in terms of methodology are presented in terms of a novel sensitivity based approach to inverse simulation that has advantages in terms of numerical accuracy and a new search-based optimisation technique based on the Nelder-Mead algorithm that can handle inverse simulation problems involving hard nonlinearities. Engineering applications of inverse simulation are presented, some of which involve helicopter flight control applications while others are concerned with feed-forward controllers for ship steering systems. The methods of search-based optimisation show some important advantages over conventional gradient-based methods, especially in cases where saturation and other nonlinearities are significant.

The final discussion section takes the form of a critical evaluation of results obtained using the chosen methods of system identification, parameter estimation and optimisation for the modelling and control applications considered. Areas of success are highlighted and situations are identified where currently available techniques have important limitations. The benefits of an inter-disciplinary and applications-oriented approach to problems of modelling and control are also discussed and the value in terms of cross-fertilisation of ideas resulting from involvement in a wide range of applications is emphasised. Areas for further research are discussed.

Acknowledgements

Many of my colleagues, past and present, in the Department of Electronics and Electrical Engineering, the Department of Aerospace Engineering, the Faculty of Medicine and the Institute of Biological and Life Sciences (IBLS) at the University of Glasgow have contributed to the research presented in this thesis. Their interest, support and commitment have been very important. Even more significant is the contribution of the many research students and other students undertaking project work whom I have supervised over the years within the Department of Electronics and Electrical Engineering and the inter-departmental Centre for Systems and Control. Their efforts have been vital to the success of much of the work and their important contribution to the research is therefore acknowledged.

Much of the more recent research reported here has evolved through close collaboration with my colleague and former research student Dr Euan McGookin, now a Senior Lecturer in the Department of Aerospace Engineering. He and I have jointly supervised a number of research students and his contribution has been particularly important.

Others, whose influence was especially significant in terms of the direction taken by my research in its early stages, include Dr Frank Moran and Dr Allan Pack, both formerly of the Centre for Respiratory Investigation at Glasgow Royal Infirmary, and Professor Jay Rosenberg of IBLS. At a later stage Professor Gareth Padfield (now of the University of Liverpool and formerly with the Royal Aerospace Establishment, Bedford and the Defence Evaluation and Research Agency) was influential in the development of my interests in helicopters. This has led, more recently, to fruitful collaboration with Dr Douglas Thomson of the Department of Aerospace Engineering.

Research grants and other support provided from a number of different sources, particularly from the UK Research Councils (EPSRC and BBSRC), the Wellcome Trust, the Royal Aerospace Establishment (Bedford), the U.K. Defence Evaluation and Research Agency, the UK Ministry of Defence, the British Council and the U.S. Office of Naval Research (ONR), are gratefully acknowledged.

I am grateful to successive Deans of the Faculty of Engineering and Heads of Department in Electronics and Electrical Engineering at the University of Glasgow for their support. I also wish to give thanks for the support received during periods of sabbatical leave spent at the Department of Biomedical Engineering, University of Southern California and at the Technical University of Vienna. The ongoing support of the California State University Chico, where I currently hold the honorary position of Adjunct Research Professor, is gratefully acknowledged.

David J. Murray-Smith.

Preface

This thesis is concerned with methods of system identification, optimisation and inverse simulation applied to problems of nonlinear system modelling and also the application of optimisation and inverse simulation methods to problems of engineering systems analysis and design. Optimisation techniques are of central importance to much of the work described, which is strongly applications oriented and involves a range of problems from engineering and physiology.

The thesis involves a selection of papers published mostly in peer-reviewed journals, together with a few in refereed conference proceedings. The papers submitted within the hard-copy version of the thesis are accompanied by a review, organised in nine sections, which explains the relationship between the different published studies and attempts to place the whole work in perspective.

The first section of the review relates mainly to issues of motivation and methodology. Discussion of practical applications of the techniques are presented in subsequent sections and a final discussion section links together some of the most significant issues that are believed to arise from work involving these different application areas. Suggestions of topics for future research are an important part of that final discussion section.

The forty-one original contributions, which form the central part of the hard-copy version of this thesis, are indicated within the list of original publications using bold type to distinguish them from other (supporting) publications. When mentioned in the text, these included publications are again shown using bold type (e.g. **submitted paper** [**2**]). These publications have been chosen to provide a framework of detailed information to support statements and claims made within the review. The other papers included in the list of original contributions (shown, for example, as *supporting paper, [4]*) provide additional detailed evidence or describe further practical applications.

The amount of information included in each section of the review depends upon the extent to which individual topics are covered in the relevant submitted papers. In cases where important information on background, methodology, results or applications appears only in the supporting publications there is more detail in the corresponding section of the review. Thus the level of detail in different sections of the review is not entirely uniform and it is important that all sections of the review be read together with the relevant submitted papers.

Contents

1. Introduction

1.1 Integrated Systems and their Significance in Engineering and Physiology

Mathematical and computer-based models provide the foundation of most methods of engineering design and are of fundamental importance in many different areas of science. One important factor that influences research on modelling is the steady increase in complexity of the models required for new and existing applications. For example, one common factor in the investigation of physiological systems and the analysis and design of modern engineering systems is the fact that in both these fields there has been a rapid growth, in recent years, in our understanding of the importance of integrated systems and of the benefits of system integration within design.

It has for long been understood that physiological systems are highly integrated dynamic systems and involve complex interactions which result from millions of years of evolution. However, the significance of physiological system integration in terms of system modelling and the complexities of physiological control mechanisms has only been fully appreciated during the past half century as attempts have been made to apply quantitative methods of investigation to biological systems. In this case clever experimental design can be applied, to some extent, to reduce the level of coupling and interaction within the system. This often involves attempting to open feedback loops or isolate subsystems by cutting or blocking communication channels.

The widespread introduction of embedded systems and other forms of computer-based control in recent years, in many different areas of engineering, has led to a very rapid increase in the complexity of man-made systems for many applications. For example, digital “fly-by-wire” control systems are now commonplace, both in civil and military aircraft and this inevitably leads to new levels of complexity in terms of interactions, not only within the on-board systems of the aircraft but also between the pilot and the vehicle and between different vehicles. Novel features, such as “carefree manoeuvring”, assist aircrew in avoiding potentially hazardous situations and thus help to improve safety margins in civil aircraft but, inevitably, this is done at the cost of additional complexity and an increase in the level of integration. This, in turn, introduces further complexities in terms of design since full design integration requires design teams that are organised so that technical and economic factors may be traded. This, in turn, allows the overall performance to be more fully optimised and design cycle times to be reduced.

Current trends in aeronautical engineering make it very probable that multidisciplinary issues involving the elastic airframe, the flight control system, the propulsive control system and physiological “biodynamic” factors involving the pilot will combine in future to an extent not previously encountered in aircraft design. For example, low frequency modes of structural vibration are likely to need an active structural mode control system that is fully integrated with the primary flight control system as the bandwidths of these two systems are likely to overlap significantly. Similar situations where “control-configured” solutions involving system integration and multidisciplinary design issues are becoming increasingly important can be identified in other application areas, such as robotics.

1.2 System Modelling Issues for Integrated Systems

It is clear that with integrated design the systems that have to be brought together do not exist in hardware terms when initial design decisions are being made. This contrasts with traditional approaches to control system design where procedures normally involve the development of a controller for a "plant" which already exists, or a plant that has been designed in detail prior to control issues being considered. In such a traditional approach direct comparisons between the plant model and the system are often possible. In contrast, within the integrated approach to design, control is no longer a second stage in the design process and the design of the control systems cannot be separated from other stages of the overall design. Although this requires a new approach it need not, however, produce insuperable difficulties because it is normal to start the design process for an integrated system using some form of highly simplified conceptual model that only includes features that are considered as essential. This initial model is intended only to provide a basis for the evaluation of major design options and for making preliminary design decisions. As soon as more detailed and tested models become available they are used in place of this conceptual description.

Within multidisciplinary design teams the concurrent consideration of critical constraints is central to this integrated design process and this implies a need for models of the highest possible quality for each stage of the development. There is also a need for software tools for dynamic modelling and simulation that can be integrated with other design software. Currently available tools do not appear to be able to handle adequately all the necessary technological areas and, inevitably, some initial models may prove to be inappropriate for their intended application.

As an illustration, methods of computational fluid dynamics and finite element modelling are widely used in many areas of engineering. When such tools are used for the modelling of elements within a larger system involving a number of sub-systems it may be essential to derive reduced-order descriptions to help avoid the effects of major computational overheads when sub-models are being combined to provide a more integrated description of the larger system. This model reduction process, inevitably, introduces approximations and simplifications which must be introduced with caution.

Advanced computational tools of this kind, such as finite element techniques, are also being used increasingly for physiological modelling. Examples of this include investigations of the cardiovascular system and pulmonary airways. In this case the need for reduced models arises because of the inevitable difficulties that arise if the computational timescale for a model is orders of magnitude greater than the timescale convenient for the analysis and decision-making processes of the investigator. In the case of engineering design processes it is equally important that sub-system models should be capable of running in timescales that are well matched to the thought processes of human designers. At each stage of a project, whether it involves engineering design or open-ended scientific investigation, it is important that any models being applied are appropriate for the intended application. Models are never unique.

The availability of appropriate mathematical and computer-based models is of clearly of central importance, both for the analysis of existing systems and for the design of entirely new systems. More than ten years ago the UK Office of Science and Technology Report by the Technology Foresight Panel for the Defence and Aerospace Sector (Anonymous, 1995) included a statement that:

"…..Improved modelling of physical and manufacturing processes will improve our ability to predict the behaviour, costs and risks of future systems, and dramatically reduce the development timescale".

That government report also states:

"…..While it is essential that modelling and simulation is supported by validation trials, improvements will reduce the need for costly and time-consuming developmental testing".

Thus, while creating an expectation that improved modelling methods can assist significantly in the development of future systems, the report is also emphasising the importance of model validation but is stating clearly a belief that improved modelling techniques can reduce the time required for the new product or process to clear the final testing or commissioning stage.

Although full system models are never available at the earliest stages of design (or at the start of a biological system investigation) it has to be recognised that some information may exist about sub-systems and that some sub-model descriptions may be available from previous investigations of a similar kind or from an available library of documented model components. In many cases valuable data may also exist from earlier trials and experiments and, in the case of engineering systems, from hardware-in-the-loop simulations studies or from commissioning tests of existing systems of a similar kind.

1.3 Questions of Model Quality

In general, the quality of a model has a direct influence on the quality of the final solution, whatever the application. For applications involving automatic control, the models are usually dynamic in form, involving combinations of linear or nonlinear ordinary or partial differential equations and algebraic equations or may be based on differential algebraic equations. Dynamic models, which can also be in discrete form based on difference equation descriptions, are also important in many other fields of research, including physiology.
Although many models may be developed using physical, chemical, or biological principles in the initial stages, the use of experimentation is important for checking the significance of underlying assumptions or simplifications and also for estimating appropriate sets of parameters. This experimental approach to modelling is also of central importance in establishing the suitability, or otherwise, of a given model for an intended application (the so-called "model validation" problem) and forms an important part of the work presented in this thesis. The approaches discussed are highly relevant both to engineering system model development and to the modelling of physiological systems.

System identification, which is the broad term used to describe the processes of experimental modelling, is generally considered to be a mature field and classical methods of identification involve linear discrete-time models within a stochastic framework. The aspects of the research described in this thesis that relate to the use of identification, parameter estimation and optimisation techniques are concerned with model development generally and the applications are not concerned exclusively with control. They involve, mainly, nonlinear continuous-time models and are also concerned with other areas of engineering system design and with physiological system modelling. Objectives from within these different application areas include hypothesis testing, the development of inferential measurement methods and also real-time simulator development.

In some forms of continuous-time system models the physical interpretation of the model structure and parameters can be made more direct than for other possible model structures, with important benefits in terms of interpretation. Together with issues involving experimental design and the choice of test signals for the estimation of parameters, the choice of model structure can contribute in an important way to the overall robustness of models that are established experimentally. This aspect of modelling and related issues of structural and parameter sensitivity and identifiability receive attention within a number of the application studies. The process of extracting data from system and sub-system tests for model development and refinement is not a trivial task and the whole iterative process of development in the presence of uncertainties raises many important issues and emphasises the fact that there are no generally accepted approaches to the problem of model validation.

Techniques of inverse simulation, which are mostly based on optimisation methods, are well-established in specialised fields such as aircraft handling qualities investigations but, until very recently, were almost unknown in other modelling and control application areas. However, these methods do appear to offer an interesting alternative to other approaches to model inversion, especially in the nonlinear case, and have been the subject of a number of developments in terms of methodology and several applications studies that are included in the thesis. The possible benefits of using inverse simulation methods for the design of combined feed-forward and feedback control systems for cases where actuator saturation and other hard nonlinearities are present, has also received particular attention.

1.4 Optimisation Issues

In terms of optimisation problems, the design, experimental tuning and performance evaluation of complex closed-loop control systems has much in common with the use of optimisation techniques within the model development process and it is therefore helpful to consider these two areas together within the thesis. Although gradient-based methods remain important, the complexity of many practical problems of modelling and control means that it is impossible to establish a global optimum using gradient methods alone. Techniques such as simulated annealing, genetic algorithms and genetic programming provide important benefits within the system modelling and control system design areas and are applied to a number of different problems. The importance of these global optimisation tools is likely to become even more significant as very large integrated systems become more commonplace.

Another topic, considered both in the context of system modelling and control and closely related to optimisation, is parameter sensitivity analysis, which was the subject of much research in Eastern Europe in the 1960s and 1970s but has been rather neglected elsewhere. It has been found that insight gained from parameter sensitivity information can be of value not only in the development and refinement of system models (e.g. through investigation of model robustness and the design of appropriate test inputs), but also in feedback system design and in controller tuning.

1.5 Overview

This thesis presents results of almost forty years of work involving research in system modelling, optimisation, system identification, system simulation and control. The research is strongly applications oriented and involves investigations which have physiological objectives as well as much work which fits within the more conventional areas of engineering applications. Following this introductory section, the presentation and discussion of the material in the submitted papers has been organised under the main headings shown below:

a) Optimisation, System Identification and Parameter Estimation in the Development of Dynamic Models.
b) Inverse Simulation for System Modelling.
c) Issues of Quality and the External Validation of Dynamic Models
d) Optimisation Methods in Nonlinear System Modelling and Nonlinear Control System Design Applications
e) Inverse Simulation for Control System Design Applications
f) Sensitivity Function based Optimisation for Controller Tuning
g) Other Related Work involving System Modelling and Control Applications

The final discussion section of this review takes the form of a critical evaluation of results obtained using the chosen methods of system identification, parameter estimation and optimisation for the various system modelling and control applications considered. Areas for further research are discussed, especially in the context of integrated systems.

2. Optimisation, System Identification and Parameter Estimation in the Development of Dynamic Models

It has already been emphasised in the introduction that models need to be appropriate for their intended purpose. It is also clear that models of a given system are never unique. Model development is an iterative process involving repeated attempts at formulation, testing and re-testing. The form of model adopted at a particular stage in a project must therefore take account of the objectives, the amount of detail appropriate in the model at that stage of the work and the uncertainties in the information available about the real system. In some situations, particularly when modelling existing systems or sub-systems, there may well be a need for experimental investigations before any form of highly detailed quantitative model is developed.

2.1 Optimisation Techniques in System Modelling

System identification and parameter estimation techniques involve the use of observations and measured response information from a real dynamic system to develop mathematical and computer-based models that represent the characteristics of that system. The model has a general form which involves a number of ordinary differential or difference equations and an associated set of parameters which have to be estimated. In general, the structure (as defined by the number of differential equations and the form of any associated algebraic relationships) also involves uncertainties and the most appropriate structural form may have to be established from measured response data.

The most widely used approach is based on least squares minimisation of the difference (error) between the model response and the measured system response. The process of deciding on the most appropriate structure for the model usually involves background knowledge and physical understanding of the system under investigation, as well as examination of the available response data. Once an initial model structure has been established and uncertainties in that chosen structure have been critically assessed, the parameters of the model can be adjusted in an iterative fashion using a specified optimisation cost function. The iterative processes of parameter adjustment continue until the responses of the model match those of the real system to some pre-defined level based upon values of the chosen optimisation criterion.

Dynamic models used in practical engineering applications are usually nonlinear in the parameters. In such cases a nonlinear optimisation approach must be applied for determining the most appropriate set of parameters to ensure that model responses match experimental data. Many nonlinear optimisation techniques and methods for iterative solution of nonlinear equations have been developed and general information about the relevant algorithms may be found in sources such as Press et al. (1986) and Nelles (2001).

Nonlinear optimisation and the iterative solution of nonlinear equations are challenging processes due to the potential presence of large numbers of local maxima and minima. Therefore, it is possible that many sets of locally “optimal” parameters

may be determined from experimental test data and care must be taken to find the set that corresponds to the global optimum solution. Also, because more than one possible solution can exist, in contrast to the unique solutions typical of linear optimisation methods, nonlinear optimisation techniques are iterative in nature. As a result, nonlinear optimisation methods usually cannot be considered for on-line applications.

One very important factor in nonlinear optimisation is the choice of the initial parameter set. Although a random or arbitrary initial set of parameters may lead to convergence to an optimum, the selection of a favourable set of initial parameters on the basis of prior knowledge can increase the speed of convergence considerably.

Nonlinear optimisation methods can also be classified as *Local* and *Global* methods (Nelles, 2001). Although they converge to local optima, local methods often converge to points that are close to the initial parameter set, particularly with methods in which search directions are obtained from first and second-order derivative information. Such algorithms thus tend to become stuck at a local minimum or maximum and an extremum in another part of the parameter space may be neglected. Global nonlinear optimisation methods can overcome this type of difficulty and rely on the inclusion of random components that help the algorithm to avoid becoming trapped at local optima. Well known global optimisation techniques include *simulated annealing*, (SA), described in Kirkpatrick, Gelatt and Vecchi (1983) and in van Laarhoven and Aarts (1987), and *evolutionary* algorithms such as the *genetic algorithm*, (GA), details of which may be found in Holland (1975) and Goldberg (1989). The techniques of simulated annealing and evolutionary computing are reviewed in more detail in Section 5 of the thesis.

It is important to note, however, that global methods involve some form of search of the whole of the parameter space and computational overheads are therefore significant, with relatively slow rates of convergence. Using local methods, it is also possible to obtain a more global optimum using a “multi-start” approach. In this, several local optimisations are carried out with different initial parameter sets. The best of these solutions is then taken as the “global” solution. A further possibility is to use global and local methods together, with global techniques locating the region around suitable local optima and a local optimisation method then being used to find a better final estimate.

Local optimisation approaches that employ gradient information are widely used. The simplest gradient-based method is the *Steepest Descent* approach. This method does not require second-order derivatives of the loss function, but is known to converge slowly. *Newton’s method* involves use of the inverse of the Hessian matrix and depends on second-order derivatives, which may introduce significant computational overheads. Newton’s method is also computationally demanding because it involves matrix inversion. Use of the *Quasi-Newton method* reduces the computational complexity by replacing the inverse Hessian by an approximation.

The Newton and Quasi-Newton methods have good convergence properties on the basis of the number of iterations but for large problems such methods are computationally demanding. *Conjugate-Gradient* methods, such as the *Fletcher-Reeves* algorithm, provide an alternative approach to local optimisation that can be

less computationally demanding. Instead of using the Hessian matrix or an approximation to the Hessian, conjugate-gradient methods involve an approach where an estimate of the search direction is computed more directly. Conjugate gradient methods typically require more iterations than the Quasi-Newton and Newton methods to converge to an optimum. However, due to their computational simplicity, the overall speed of these algorithms is better.

Nonlinear least squares methods are preferred for cases in which the loss function is of the sum-of-squares type. Two well-used nonlinear least-squares methods are the *Gauss-Newton* method and the *Levenberg-Marquandt* method. As discussed in the text by Soderstrom and Stoica (1989) the Gauss-Newton algorithm is closely associated with the general and modified forms of the *Newton-Raphson* algorithm for solution of numerical search problems. The Newton-Raphson algorithm provides the basis of two of the traditional approaches to inverse simulation methods, which are discussed in Sections 3 and 6 of the thesis.

The text by Raol, Girija and Singh (2004) provides a very useful review of least squares methods in the context of system modelling, system identification and parameter estimation. This treatment of optimisation methods establishes links between the properties of classical gradient-based optimisation techniques and methods used in the modelling of dynamic systems, such as the *Generalised Least Squares* and *Nonlinear Least Squares* methods. This, in turn, leads to detailed discussion of the *Equation Error* and *Output Error* methods that are applied in the helicopter system identification applications described in Section 2.5.1.

The simplest general-purpose nonlinear local optimisation techniques are termed *Direct Search* methods and make use only of loss function values in their search for local optima. Such methods include the *Simplex Search*, *Hooke-and-Jeeves* and *Nelder-Mead* methods. These methods are typically rather slow to converge and are often only used if the derivatives of the loss function are not available or can be estimated only at considerable computational cost. The Nelder-Mead approach is applied extensively in Section 3 in the context of an improved method of inverse simulation for modelling and control applications.

The optimisation of the structure of a model can also be regarded as a form of optimisation of the complexity of the model since “model complexity” relates to the number of separate equations and thus adjustable parameters present. Also, with more parameters, a model increases in flexibility since the number of possible forms of behaviour that could be exhibited by the model increases. A model that is too simple will not capture the behaviour of the system and will give poor predictions. Also, if the amount of data available for parameter estimation and subsequent testing of the model is inadequate a relatively complex model may perform badly.

Thus, the complexity of a model must always be appropriate for the intended task. Optimising the complexity of a model is closely linked to the question of model validation (Section 4) where the performance of a given model is assessed. An important feature of the model validation process is that the model performance is assessed using a “test” dataset that is not the same as the “training” dataset used in estimating the structure and parameters of that model. The importance of this approach is that, in this way, the *generalisation* ability of the identified model may be

assessed in a critical fashion. Generalisation is the model capability in terms of accurate prediction of the system output when presented with forms of input that were not used in the development of the model.

The terms *under-fitting* or *over-fitting* may be used in discussion of models that perform poorly. If the test data are estimated badly and the model appears to be too simple, the situation is generally described as involving under-fitting. For a case in which a relatively complex model is used and the training appears to be satisfactory, but the generalisation is poor, the situation involves over-fitting. The model parameters may be biased by noise within the data used for identification, or the model has been "trained" correctly but the interpolation between data points is poor.

2.2 System Identification and Parameter Estimation

2.2.1 Issues of identifiability

The precision of any parameter estimate is expressed in terms of its variance and this is a function both of the experiment and of the estimation technique used. Often the objective is to obtain unique and reliable estimates of all of the parameters of a model. It is important to investigate whether or not this is possible for a given structure of model and a given form of experiment. This involves investigation of *identifiability* and it is important to establish whether or not potential identifiability problems exist before selecting an identification method and considering issues such as experimental design.

Global or *structural unidentifiability* is a situation in which a model has an excess of parameters so that some specific parameters cannot be estimated uniquely for any possible input stimulus and design of experiment. Structural identifiability is only a minimal necessary condition for obtaining unique estimates of model parameters. As the name suggests it depends on the structure of the model and not on numerical values of parameters or on the design of the identification experiment. Structural unidentifiability arises when a model has too many parameters to allow all of them to be found for any possible input stimulus.

Pathological or *numerical unidentifiability* is a term that describes a structurally identifiable model that is being used with experimental data that is inappropriate for the intended application. This may be because the length of the available record is short in comparison with the dominant time constants or the period of oscillatory components of the response. It can also arise if the measured response data are very heavily corrupted by noise.

Bellman and Åström were among the first (Bellman & Åström, 1970) to formulate and discuss the problems of structural identifiability. They presented their findings in the context of biological compartmental models but the results are applicable to a wide range of other identification problems. They showed that classical transfer function theory could be used as a basis for the investigation of identifiability. If each coefficient of the transfer function matrix is expressed as a combination of the unknown parameters, a set of nonlinear equations is defined. Bellman and Astrom showed that the model is identifiable in a global sense if these equations have a unique solution.

Numerical (or "pathological") unidentifiability, or situations approaching this, arise when a model is found to be structurally identifiable but cannot give valid results for a given set of experimental data. This may be as a result of inaccurate measurements, noise or poor experimental design. Beck and Arnold (1977) have shown that model parameters can be estimated only if the parameter sensitivity coefficients for the output variable with respect to each parameter are linearly independent over the range of observations. In simple cases, problems of numerical unidentifiability may be deduced from the time histories of the sensitivity coefficients. The problem can also be investigated more systematically by examining the sensitivity matrix $\boldsymbol{X}$ and the closely associated parameter information matrix $\boldsymbol{M} = \boldsymbol{X}^T\boldsymbol{X}$. This type of analysis allows more complex interdependencies to be investigated. Pathological unidentifiability is linked to linear dependence of the columns of $\boldsymbol{X}$ and this is reflected in the determinant of matrix $\boldsymbol{M}$ or in the condition number of the matrix (the ratio of the largest eigenvalue of $\boldsymbol{M}$ to the smallest eigenvalue of $\boldsymbol{M}$). If the condition number is large, or if the determinant is small, the confidence region for the estimates is large and the parameter estimates are therefore not well defined.

The matrix $\boldsymbol{M}^{-1}$ is also important in terms of tests for numerical identiafibility. This matrix, the inverse of the parameter information matrix, is known as the dispersion matrix and is commonly denoted by $\boldsymbol{D}$. The determinant of $\boldsymbol{D}$ can be shown to be a useful indicator of numerical unidentifiability.

Correlations between pairs of parameters can be investigated using the parameter correlation matrix $\boldsymbol{P}$ (Beck & Arnold, 1977). This matrix is commonly defined in terms of its elements:

$$p_{ij} = \frac{m_{ij}^{-1}}{\sqrt{m_{ii}^{-1} m_{jj}^{-1}}} \tag{2.1}$$

where p_{ij} is the element of $\boldsymbol{P}$ in row i and column j and m_{ij}^{-1} is the element of $\boldsymbol{M}^{-1}$ in row i and column j. The matrix $\boldsymbol{P}$ has diagonal elements which are unity and all the off-diagonal elements lie between -1 and 1. Conditions close to unidentifiability are indicated if the modulus of one or more of the off-diagonal terms is close to unity, with a value of 0.95 being regarded as a limiting value (Beck & Arnold, 1977). Small values of the off-diagonal elements of $\boldsymbol{P}$ indicate that the parameters are essentially decoupled.

2.2.2 Design of experiments and the selection of test-input signals

In the design of appropriate test signals for system identification and parameter estimation it is essential to have a quantitative basis upon which test signals can be compared. It is also customary to assume that the estimator is efficient (Silvey, 1975) and that these aspects can be investigated independently of the estimator. In the work presented here, test signal design involves the use of quantities such as the parameter information matrix and the dispersion matrix, both of which have theoretical origins in the Cramer-Rao bound. Through the Cramer-Rao bound the variance of parameter estimates may be related to elements of the dispersion matrix $\boldsymbol{D}$, which is defined as

the inverse $\boldsymbol{M}^{-1}$ of the parameter information matrix $\boldsymbol{M}$. Since the elements of the parameter information matrix depend on the parameter sensitivity matrix $\boldsymbol{X}$, which can be found from measurements, the elements of $\boldsymbol{D}$ can be derived from the measured responses. In general terms, inputs giving a dispersion matrix with small elements are to be preferred over inputs producing large values in these elements. This has led to test input design algorithms that minimise some appropriate function of the dispersion matrix or of the parameter information matrix.

The parameter information matrix $\boldsymbol{M}$ provides the basis for a number of measures of the quality of an experiment using relationships which are of the general form

$$J = f(\boldsymbol{M}) \tag{2.2}$$

where f is an appropriate scalar function. One widely used criterion for experiment design is the so-called D-optimal criterion (Federov, 1972) which involves the dispersion matrix and has the form

$$J_D = \det(\boldsymbol{M}^{-1}) \tag{2.3}$$

Use of this criterion results in a test signal which puts equal emphasis on the estimation of all of the parameters. In cases where a subset of parameters is more important, use of a truncated D-optimal design criterion of the form

$$J_{Dt} = \det(\boldsymbol{M}_{ii}^{-1}) \tag{2.4}$$

has been advocated (Hunter, Hill & Henson (1969)), where $\boldsymbol{M}_{ii}$ is a sub-matrix of the full information matrix and refers only to the i parameters of interest. Use of the truncated D-optimal criterion developed by (Hunter Hill & Henson, 1969) involves calculations based on the elements of the sensitivity matrix $\boldsymbol{X}$ which themselves are dependent on the values of model parameters. This means that it is possible to use the criterion only to investigate and compare different forms of experiment and test signal designs in a general fashion. Use of the criterion to generate an experiment which is optimal for a particular subject is not possible because exact parameter values are not known *a priori.*

2.2.3 Identification issues for point process and hybrid systems

Hybrid systems involving continuous-time signals and variables described on a discrete-event basis are now seen as being of considerable practical importance in many different fields. Such systems arise in neurophysiology and in the 1970s Professor Jay Rosenberg of the Institute of Physiology at the University of Glasgow recognised that work by Professor D.R. Brillinger at the University of California, Berkeley, on the statistical analysis of point processes was of potential importance for the experimental investigation of elements of the peripheral nervous system. The short duration of the nerve impulse (in comparison with the time interval between impulses) and the wide range of observable discharge patterns forms the basis for considering a sequence of nerve impulses (a spike train) as a realisation of a point process.

Professor Rosenberg's interest in the system identification approach led to the establishment of an interdisciplinary research group and close collaboration with him and his colleagues over a long period of time. This involved a series of four jointly-supervised research students and several research assistants at different times. The work was concerned with the application of system identification ideas to point process systems in neurophysiology and to more complex situations involving a combination of continuous signals and point processes. This work led to a number of joint publications.

It is possible to approach the identification of point process systems and hybrid systems by converting point processes into conventional continuous data and then applying traditional time-domain or frequency-domain identification methods. This formed a successful initial step, as reported in (Maclaine et al., 1977 - **submitted paper, [1]**) and in (Rosenberg, Murray-Smith & Rigas, 1982 - **submitted paper, [2]**). However, more direct methods, working with point process data, have potential advantages, especially in the nonlinear case. Definitions of stochastic point process measures such as mean intensity, auto-intensity functions, cross-intensity functions established by Brillinger and others (e.g. (Brillinger, 1972), (Brillinger, 1975a), (Brillinger, 1975b), (Brillinger, 1978) and (Brillinger, Bryant & Segundo, 1976)) allow spectral interpretation of the point process case, with spectra defined in terms of the Fourier transforms of the auto- and cross-covariance densities. Thus the cross-spectrum between two point processes can be defined. Estimates of the auto-spectrum and cross-spectrum can be obtained using methods first suggested by Bartlett (1963).

The spectrum of a Poisson process may be shown to be constant and this suggests that the Poisson process can have a similar role in the identification of point-process systems as the Gaussian white-noise signal in the identification of continuous systems. The links between ordinary time series and point-processes have been the subject of detailed discussion in (Brillinger, 1978). As is shown in our 1982 paper (Rosenberg, Murray-Smith & Rigas, 1982 – **submitted paper, [2]**), it is possible to define a quantity that is a transfer function for a point-process system. This form of linear point process description is discussed further by us (Halliday, Murray-Smith & Rosenberg, 1992 – **submitted paper, [3]**), where it is pointed out that the implementation of spectral estimation is of central importance in the identification of a point process system. Also it is shown in this paper that it is possible to determine of the degree of linear correlation between input and output point processes through determination of the *coherence*. This quantity is estimated using an expression which involves calculation of the auto-spectra of the signals and the cross-spectrum between them. It is shown to be analogous to the expression for coherence commonly applied for continuous systems and signals.

In the case of systems involving a mix of continuous signals and point-processes it was found that Jenkins (1963) had suggested a method for determining the cross-periodogram between a continuous signal and a point process and this allows the cross-spectrum to be found directly. This, in turn, allows estimation of the coherence in the hybrid case. The application of this approach to the experimental study of muscle spindle receptors is discussed further in Section 2.4 and in (Rosenberg, Murray-Smith & Rigas, 1982 – **submitted paper, [2]**), (Halliday, Murray-Smith & Rosenberg, 1992 – **submitted paper, [3]**) and also in (Murray-Smith & Rosenberg,

1983 – *supporting paper, [4]*). Other neurophysiological applications are described in (Davey et al., 1986 – *supporting paper, [5]*), in (Conway et al., 1990 – *supporting paper, [6]*) and in (Amjad et al., 1989). The development of tutorial software on methods of analysis for point-process signals, which includes a simulation program involving a simple nonlinear neural encoder model, is described in (Murray-Smith et al., 1995 – *supporting paper, [7]*). It is believed that the methods developed for this work on the peripheral nervous system have broad applicability to other physiological systems involving point-processes or a combination of continuous signals and point-processes. It is probable that there are also many potential applications in other fields.

2.2.4 Local model networks

Artificial neural networks (ANNs) have attracted much attention for modelling applications, both in terms of the conventional multi-layer perceptron (MLP) and the radial basis function type network (RBF). Neither type of description can provide much insight about the physical form of the underlying system and do not allow prior knowledge to be incorporated easily into the identification process. However ANNs do provide an approach that can be extended to allow a network of local models to be defined which can provide useful physical interpretations in some situations.

The reasoning behind the introduction of multiple model networks is to be able to split a complex and inherently nonlinear modelling problem into a number of smaller and simpler tasks. Each of the resulting sub-problems is then handled on a local basis by a simpler sub-model. In this way the operating space of the system is effectively partitioned into a number of local regions or "regimes" and the global model is constructed through an appropriately weighted combination of the outputs from each of the local models.

Several different multiple modelling approaches have been applied to the nonlinear system identification problem. For example, fuzzy logic has been used to partition the operating space using a set of rules and membership functions derived using prior knowledge (and especially qualitative knowledge) about the corresponding real system. The so-called TS modelling approach, introduced by Takagi and Sugeno (1985), is one important example of this type of model involving a set of local models based on expert qualitative knowledge.

Prior qualitative knowledge seldom provides enough information for the development of a successful model. The use of empirical data is usually essential and a combined approach of this kind is often described as *neuro-fuzzy* modelling. The most important point is that, in comparison with neural network methods, fuzzy networks are easier to interpret. More details of this approach can be found in the work of Jang and Sun (1993) and Pfeiffer and Isermann (1994).

Another approach to the problem of defining a multiple model network involves the *operating regime* based type of methods developed in the work of Johansen and Foss (e.g., (1993)). This and other related work led to the Local Model Network (LMN) architecture is discussed in detail in the PhD Thesis of Roderick Murray-Smith (1994) and examined further in the edited volume by R. Murray-Smith and T.A. Johansen (1997), which includes a review of the relationship between LMNs and other approaches including RBF networks, Takagi-Sugeno fuzzy models and probabilistic

methods involving hierarchical mixtures of experts (see e.g., (Jordan & Jacobs, 1994)).

The LMN can be interpreted as an extension or generalisation of the normalised form of RBF network. Instead of employing simple weights in the output layer, more complex weighting is used through the introduction of local models which are usually dynamic in form. In principle, the local models may have any form, but local linear models are often used as these are easier to implement and interpret than more general nonlinear descriptions. An advantage of this approach is that each local model, if carefully chosen using prior knowledge, can cover a significant part of the operating space. Each local linear model is usually established for a specific equilibrium operating condition. An LMN network of specified accuracy can therefore usually be constructed using a smaller number of basis functions than the equivalent RBF network, thus giving better computational efficiency. The interpretation of results and analysis of the structure of the overall model is also usually more straightforward. Engineers are generally experienced in the use of linear models, and most engineering systems are designed for operation near to equilibrium conditions for much of the time. This means that linear methods can be applied in the identification of the local models and the fact that the models are usually identified for conditions close to equilibrium suggest that the experimental testing of the real system is likely to be relatively straightforward.

A local model network involving *M* local models may be described by an equation of the form:

$$\hat{y} = \sum_{i=1}^{M} \rho_i(\phi)\, f_i(\psi) \tag{2.5}$$

where $\hat{y}$ is the output prediction, the $\rho_i(\phi)$ factors are scalar functions of the *scheduling vector* ϕ and $f_i(\psi)$ represents the outputs of the local models for input vector ψ. The functions $\rho_i(\phi)$ are termed *validity functions* and are equivalent in some respects to the basis functions of an RBF network and are similar to membership functions of a fuzzy network.

A validity function transforms its input to a value between 0 and 1. It has a smooth form with, a maximum at the middle of the range over which it applies and the set of *M* validity functions forms a partition of unity. The activation of a validity function decreases with increasing distance of its input from the point at which the maximum occurs. Although there are many possible functions (such as normalised Gaussian bells) that could be used as validity functions, one common choice is a set of third-order B splines which are composed of quadratic polynomials. A set of B-splines can be defined recursively (de Boor, 1978) and although they are, by definition, one-dimensional functions they can be extended to cover a multidimensional space (see e.g., (Kavli, 1993)). The use of functions such as B-splines ensures a localised region of activity for each local model and smooth interpolation between neighbouring models (Gollee, 1998).

The scheduling vector $\phi(t)$ must be chosen with care. It must represent the nonlinear properties of the underlying system since its function, essentially, is to define the operating point so that the appropriate local models can be applied at each time instant. It can be related either to the output of the system or to the input or some combination of input and output (Gollee, 1998).

The training process within an LMN involves two stages. Firstly, the number, position and shape of the validity functions must be established and this is, effectively, the identification of the model structure. Then parameters of the local models need to be found, usually through the application of least squares methods. These parameters can either be optimised globally or locally. In the *global learning* approach the parameters for all the local models are optimised simultaneously whereas in the *local learning* approach the parameters of each local model are optimised separately. Following successful identification of the validity functions and estimation of parameters of the local model network the overall model can be constructed from the local models through a process of "blending".

The LMN architecture is suitable for nonlinear dynamic systems where there is prior knowledge of the real system and empirical data may be collected through tests. The use of local linear models is especially appropriate for systems where prolonged periods of operation occur near steady-state operating points where experimental data can be collected in the necessary quantities. However, it has been shown by (Shorten et al., 1999) that this reliance on local linear models may compromise the validity of the LMN architecture when the off-equilibrium dynamics of the underlying system are considered. Each local model only provides useful information about the system behaviour in a small region of the operating space. During transients taking the LMN between operating points the model is unlikely to provide an accurate representation. This may not be a serious issue when the operating point and the scheduling vector change slowly. However, in situations involving large rapid transients the model may be forced far from any operating points about which the local models were identified, resulting in poor predictions of the system output.

This problem of off-equilibrium dynamics may be overcome by including local models placed in off-equilibrium regions, but little experimental data is likely to be available for such regions. As discussed in (Shorten et al., 1999), non-unique parameterisations of the model behaviour may result in such cases. Also, the model structure for identified off-equilibrium models may be significantly different from the structure of the local models at equilibrium points. A paper by (Solak et al., 2003) shows how the incorporation of derivative information can allow potentially seamless fusion of models and points to some useful areas for further research.

A paper by (Leith & Leithead, 1999) provides a slightly different analytical framework involving linearised *velocity-based* descriptions for relating global dynamic behaviour to local models. Further investigations by (McLoone, Irwin & McLoone, 2001) have shown that it is possible to construct a velocity-based LMN from experimental test data. However, the steady-state performance of the model is less accurate and since the velocity-based framework requires the derivative of the input there may be additional problems of measurement noise if rate sensors are not available. Section 5 includes some discussion of velocity-based models for nonlinear control.

The practical use of LMN concepts in modelling applications is described in Section 2.4.2 in connection with the modelling of muscle and by (Gray et al, 1996b – *supporting paper, [8]*) for an application involving a simple laboratory process system involving two coupled tanks of liquid. This latter study demonstrates that an an inherently nonlinear system a number of models with parameters estimated at steady-state operating points can, in some cases at least, describe very effectively the behaviour of the system over the whole operating range since transients do not take the state of the system too far from the equilibrium conditions for the local models.

2.3 Applications Involving Pulmonary Gas Exchange and Respiratory System Models

Although there are many published models that describe aspects of pulmonary gas exchange processes, most early models were based on steady state assumptions. Since the 1970s the more widespread use of dynamic models based on differential equations or difference equations has provided a link between theoretical modelling and experimentation through the use of system identification methods. Dynamic models also allow full use to be made of techniques of experimental design to enhance the information content of experiments and make fuller use of transient response data.

2.3.1 A dynamic model of pulmonary gas exchange processes

The cyclic nature of ventilation has been incorporated in several lumped parameter dynamic models including one developed by (Pack et al., 1974 – *supporting paper, [9]*). This model and later refinements of it (e.g. (Murray-Smith & Pack, 1977 – *supporting paper, [10]*) and (Bache, Gray & Murray-Smith, 1981 – **submitted paper, [11]**)) were intended to be applied to simulation of the system for experimental situations involving tests of short duration. The model is compartmental in nature and consisted of a constant volume dead space compartment, representing the conducting airways, a single homogeneous alveolar compartment and a single compartment representing the tissues, as shown in Figure 2.2. In the simplest form of the model, which is still being applied in a number of applications areas, gas transfer between the tissues and the alveolar compartment is represented as a direct transfer process, without circulatory time delays. The venous blood volume is thus assumed to form part of the tissue compartment volume while the arterial blood volume is lumped into the alveolar compartment volume. In the case of carbon dioxide there is a metabolic input of gas into the tissue compartment. A full description of the model and the underlying assumptions may be found in (Bache, Gray & Murray-Smith, 1981 – **submitted paper, [11]**).

Within the dead space and alveolar compartments of this model the respiratory cycle can be viewed as involving three stages. The first stage is transfer of gas to the alveolar compartment that was in the dead space at the end of the previous breath cycle. This is followed by inspiration of the gas mixture being used as input (e.g., atmospheric air). Thus stage (2) begins when the volume of the inspired mixture is greater than the volume of the dead space compartment. Stage (3) of the cycle involves expiration.

The behaviour of this model can be described by a pair of ordinary differential equations, one for the alveolar compartment and one for the tissue compartment. For

the case of carbon dioxide, use of a linearised representation of the dissociation curve for carbon dioxide allows these equations to be written in standard state equation form. For inert gases the structure of the model is similar but slightly less complex as there is no metabolic input term. The state equation describing the alveolar compartment has a structure which changes with the stage of the breath cycle, as determined by a binary switching factor which has value one for stages (1) and (2) and zero for stage (3) . Details of the relevant equations may be found in (Bache, Gray & Murray-Smith, 1981 – **submitted paper, [11]**).

The volume of the alveolar compartment changes during the breath cycle and the value at any time instant is determined by integration of the instantaneous gas flow rate, measured at the mouth, with respect to time. The variables of particular importance for this model structure and the intended applications are the partial pressure of carbon dioxide in the alveolar $P_A(t)$, which may be regarded as a system output variable, together with the partial pressure of the relevant gas in the inspired mixture, $P_I(t)$, and the measured gas flow rate at the mouth, $\dot{V}(t)$. The latter two variables are both quantities involved in the system input.

External validation of this model was based on experiments which involved subjecting the model to an input that was identical to that used experimentally. The lung is particularly well suited to the use of such an approach since the input, which is the inspired gas flow measured at the mouth, can be measured continuously. The output of the model can be taken as the gas concentration measured at the mouth for the part of the breath cycle during expiration when gas from the alveolar compartment has completely filled the dead-space compartment volume. Over that section of the breath cycle this corresponds, approximately to $P_A(t)$ if allowance is made for the transport delay in the dead space. The ventilatory flow $\dot{V}(t)$ may be measured at the mouth using pneumo-tachographs while gas concentrations may be measured on a sampled basis during inspiration and expiration by means of a respiratory mass spectrometer. Delays need to be introduced through digital signal processing to ensure synchronisation of the signals.

The performance of this model structure and the equivalent structures when other gases were used as test inputs was tested extensively. When a relatively insoluble gas such as argon is breathed the main parameter that can be adjusted is lung volume. With a suitable value for this quantity excellent agreement was found between the model output and that of the real system both for period of argon “wash-in” and argon “wash-out”. For carbon dioxide, a number of quantities that are assumed to be constant parameters of the model have to be estimated or tuned in some way (lung volume, cardiac output, initial partial pressure of the tissue compartment, metabolic production, tissue volume and the slope of the physiological dissociation curve for carbon dioxide). A similar situation arises for the case of the equations describing oxygen exchange. In the case of hyperventilation, model results were found to agree with measurements for the case of the partial pressure of carbon dioxide in the alveolar compartment. It was also found that hyperventilation caused an increase in the amplitude of oscillations of carbon dioxide partial pressure in that compartment which paralleled the measured increase of slope of the alveolar portion of the measured expired records. This was of physiological interest and led to further simulation studies to investigate hypotheses relating to the ventilation-perfusion

concept and the mechanisms involved in producing an arterial-alveolar gradient for carbon dioxide. These simulations were also found to be of value for teaching purposes (Murray-Smith, 1990a – *supporting paper, [12]*).

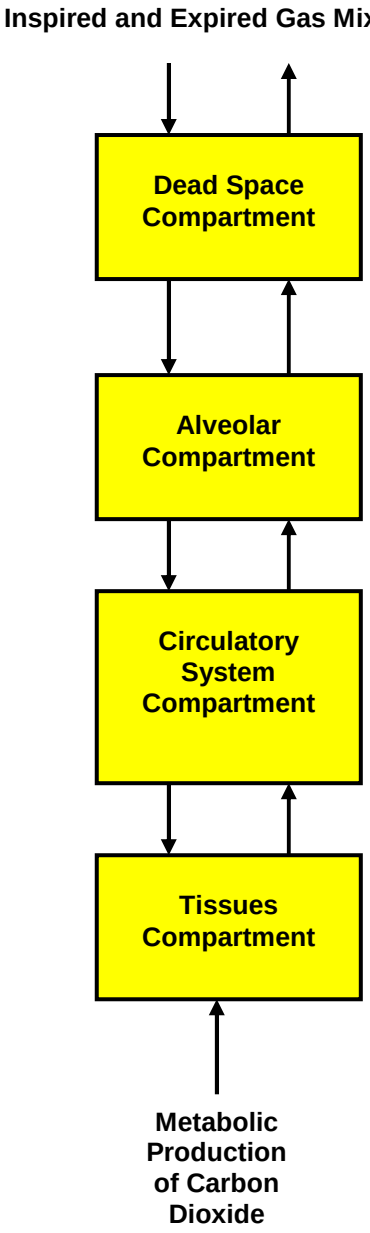

Figure 2.2: Schematic diagram of pulmonary gas exchange model for carbon dioxide.

2.3.2 System identification and parameter estimation for the gas-exchange model

Interest in the use of system identification and parameter estimation techniques with dynamic models of pulmonary gas exchange processes has focused mainly on the development of techniques for non-invasive estimation of cardio-pulmonary quantities such as the lung volume, cardiac output and metabolic production. The

compartmental model outlined above provided a basis for a major programme of computational and experimental research during the 1970s based in the Centre for Respiratory Investigation at Glasgow Royal Infirmary (as outlined in (Murray-Smith & Pack, 1977 – *supporting paper, [10]*) and described in more detail in (Bache, Gray & Murray-Smith, 1981 – **submitted paper, [11]**)). This research was aimed at clinical applications of an identification-based approach of this kind. The main objective was the development of a reliable inferential measurement technique for estimation of the blood flow through the lungs (which may be regarded as the cardiac output in normal subjects). This quantity has clinical importance and was, at that time at least, difficult to measure in a routine fashion by more conventional methods.

Estimation of parameters of the gas exchange model from experimental data involved the introduction of an autoregressive moving average noise model and the application of a modified form of the maximum likelihood method of Åström and Bohlin (1966) as described in (Bache, Gray & Murray-Smith, 1981 – **submitted paper, [11]**)

In terms of global identifiability it was found that it was possible to obtain a set of six relationships which allowed specific combinations of parameters of the model to be related to nine coefficients in the transformed equation and to the effective ventilation, which is a measured quantity. From inspection of these relationships between parameters it was shown that if the cardiac output, lung volume, metabolic production, tissue volume and the initial values of the partial pressures in the alveolar and tissue compartments are all to be estimated then the remaining two parameters of the model (which describe the dissociation curve for carbon dioxide) must be known.

Although analysis of global identifiability did not indicate any potential problems for the estimation of parameters of the homogeneous lung model, results of preliminary parameter estimation work using a modified form of the maximum likelihood method of Åström and Bohlin strongly suggested potential difficulties in terms of pathological unidentifiability. The experiments involved step function test inputs implemented in such a way that the subject had 40 seconds of air breathing followed by a sudden switch to a mixture containing 7% carbon dioxide for a further 80 seconds. Following the approach outlined in Section 2.2.1, the indications of pathological unidentifiability are clearly evident from the large values of certain off-diagonal elements within the parameter correlation matrix. For a typical data set we have:

$$
\begin{array}{c}
\dot{Q} \\ V_A \\ \dot{M} \\ V_{TC} \\ P_A(0) \\ P_{TC}(0)
\end{array}
\begin{bmatrix}
1.000 & & & & & \\
0.371 & 1.000 & & & & \\
0.584 & 0.840 & 1.000 & & & \\
0.581 & 0.841 & 0.999 & 1.000 & & \\
0.090 & -0.52 & -0.19 & -0.19 & 1.000 & \\
-0.95 & -0.42 & -0.71 & -0.71 & -0.20 & 1.000
\end{bmatrix}
\qquad (2.6)
$$

$$
\begin{array}{cccccc}
\dot{Q} & V_A & \dot{M} & V_{TC} & P_A(0) & P_{TC}(0)
\end{array}
$$

In (2.6) the parameters V_A and V_{TC} are the volumes of the alveolar and tissue compartments respectively, while $P_A(0)$ and $P_{TC}(0)$ are the initial values of partial pressures of carbon dioxide in the alveolar compartment and tissue compartment respectively. The parameter $\dot{M}$ is the metabolic production rate of carbon dioxide (in the tissue compartment) and $\dot{Q}$ is the parameter representing the total blood flow through the lungs (the cardiac output).

There are important limitations in terms of the design of identification experiments for this system due to the maximum permissible levels of concentration of carbon dioxide in the inspired mixture (P_I) and constraints in terms of the period of time over which the model may be considered a valid representation of the gas exchanging properties of the system. A further practical difficulty that affected experimental design was associated with the fact that variations of the inspired gas concentration could be achieved only using manual operation of a simple three-way tap. A decision was made that the form of signal should be restricted to square waveforms with equal intervals of air and 5-7% carbon dioxide breathing over a total period not exceeding ten minutes. In this case the problem of experimental design became one of determining the optimum frequency for switching from one gas mixture to the other.

Through computer simulation it was possible to investigate the optimum frequencies for switching of the test input gas mixture for estimation of the main model parameters, $\dot{Q}$, $V_A(0)$, V_{TC} and $\dot{M}$. Results indicated that a relatively short switching period is appropriate for estimation of the parameter $V_A(0)$ whereas a much longer period is better in the case of $\dot{M}$ and V_{TC}. In the case of the cardiac output parameter, $\dot{Q}$, which was of particular interest in the study described in (Bache, Gray & Murray-Smith, 1981 - **submitted paper, [11])**, the curve has a clear extremum within the range considered, at about a switching period of 24 breaths. Use of the D-optimal test signal design criterion, which is applied when it is important that all the parameters of a model be taken into account, gave results showing an extremum closer to the middle of the range of switching periods considered, at about 55 breaths. The best design of experiment for estimation of the complete set of model parameters is therefore not the same as the best design for estimation of particular parameters, such as the cardiac output.

Although optimal design of experiments for individual subjects is not possible because of model parameter uncertainties, sensitivity investigations have shown that the optimum switching periods are relatively insensitive to parametric variations within the normal physiological range for conditions that apply during testing.

A standard form of test signal was derived on the basis of the results of the simulation-based studies outlined above. This test signal involved alternating periods of air and a mixture containing 5-7% carbon dioxide with a switching period of two minutes and an overall test duration of ten minutes. The results of experiments involving this form of input signal showed significant improvements in terms of identifiability. A typical set of results for the parameter correlation matrix $\boldsymbol{P}$ are shown below in (2.6a) and it is clear that there are no off-diagonal terms of magnitude approaching the limiting value of 0.95 (as discussed in Section 2.2.1). The interactions between estimated parameters have thus been reduced significantly.

Clearly the use of the square wave test signal eliminates problems of pathological unidentifiability that were encountered when using the simple step function for of test input.

$$
\begin{array}{c}
\dot{Q} \\ V_A \\ \dot{M} \\ V_{TC} \\ P_A(0) \\ P_{TC}(0)
\end{array}
\begin{bmatrix}
1.000 & & & & & \\
-0.43 & 1.000 & & & & \\
0.036 & 0.067 & 1.000 & & & \\
-0.20 & 0.420 & -0.02 & 1.000 & & \\
0.021 & -0.15 & -0.01 & -0.02 & 1.000 & \\
-0.54 & 0.200 & -0.20 & -0.01 & -0.31 & 1.000
\end{bmatrix}
\qquad (2.6a)
$$

$$
\begin{array}{cccccc}
\dot{Q} & V_A & \dot{M} & V_{TC} & P_A(0) & P_{TC}(0)
\end{array}
$$

Direct examination of the form of the residuals resulting from the application of this approach showed that these are approximately white and this finding was supported by the form found for the auto-covariance of residuals. Parameter values found in tests on four subjects using the approach outlined here, which is presented in more detail in (Bache, Gray & Murray-Smith, 1981 – **submitted paper, [11]**) and (Bache & Murray-Smith, 1983 – *supporting paper, [13]*), were within the physiological range expected for these subjects and showed an acceptable level of repeatability. Encouraging results were obtained from comparative measurements using a more conventional, but invasive, method for estimating cardiac output.

Unfortunately this technique for estimation of cardio-pulmonary quantities did not lead directly to the development of new methods for routine investigation of clinical problems. This was mainly due to the relatively high cost, at the time of this development, of the computing equipment required and the additional cost of the specialist measuring equipment needed, such as respiratory mass spectrometers. However, the use of system identification and parameter estimation methods in the context of the cardiopulmonary system received further attention from a number of other research groups (e.g., (Brovko, O. et al., 1981)). The dynamic form of the gas exchange model has also been used in further research on problems of respiratory control (Greer, Jordan & Murray-Smith, 1982 – *supporting paper, [14]*), in the development of teaching software for students of physiology and medicine (Murray-Smith, 1990a – *supporting paper, [12]*) and, very recently, exercise physiology (Thamrin & Murray-Smith, 2007 – *supporting paper, [15]*).

Following the publication of papers describing applications of the dynamic gas exchange model outlined above, further work was carried out and a second model, also of lumped parameter form, was developed to allow various forms of maldistribution of ventilation and perfusion to be considered. These included features such as an alveolar dead space or a circulatory shunt. Investigations of identifiability for this inhomogeneous model for inert gases showed that neither the degree of a circulatory shunt nor the cardiac output could be estimated independently from measurements at the mouth (Bache & Murray-Smith, 1983 – *supporting paper, [13]*). However, the analysis did show that these quantities could be decoupled if measurements could be made of the gas partial pressure in arterial blood. Continuous

measurements of that type were, however, beyond the capabilities of mass spectrometry at the time when the work was carried out and this aspect was not considered further.

It has been noted (Murray-Smith, 1982 – *supporting paper, [16]*) that, in the identification of physiological systems, we are often dealing with very limited data. Also, uniform sampling may not always be possible (for example, in measurements involving samples of blood). Although not encountered in the work involving the application of system identification methods to gas exchange models, problems of sampling strategy and test signal design can be very severe in other types of physiological application (e.g. in the investigation of humoral systems). The research reported in (Bache, Gray & Murray-Smith, 1981 – **submitted paper, [11]**), with the emphasis on issues of identifiability and test signal design, represents an important contribution to the practical application of system identification and parameter estimation methods to physiological systems.

2.4 Applications Involving Neurophysiological Models.

Neurophysiology provides a few very interesting examples of situations where modelling and simulation methods have had a significant role in providing a formal basis for quantitative descriptions of real systems and in guiding the design and execution of experiments (e.g. the work of Hodgkin and Huxley (1952) on the basic processes of nerve conduction and more recent work by Prochazka and his colleagues (e.g., (Prochazka, 1996); (Prochazka, Gillard & Bennett, 1997); (Prochazka, Gritsenko & Yakovenko, 2002)) on neuromuscular control. However, most areas of neurophysiology appear to have been influenced very little by the techniques of experimental modelling.

2.4.1 Modelling of muscle spindle receptors

One area of neurophysiology where some very significant progress has been made in terms of quantitative experimental investigation involves the muscle spindle, which is believed to be an important element within the neuromuscular control system. Although control theory has provided a framework for descriptions of the function of the muscle spindle, and experimental techniques such as frequency response measurement have been applied, it is clear that little of the recent progress in muscle spindle physiology can be attributed to modelling and simulation. It is believed that this may be due in part to a failure to bring together experimental and modelling approaches and adopt a truly integrated approach to the investigation of this very complex physiological system (Murray-Smith & Rosenberg, 1983 - *supporting paper, [4]*)

Muscle spindles are receptors which respond primarily to length changes imposed on the muscles in which they are embedded. Each muscle involved with posture or the control of movement contains a number of these receptors, which lie in parallel with the load-bearing fibres. Muscle spindles consist of a number of specialised muscle fibres (the intrafusal fibres) which lie in parallel with each other. The intrafusal fibres are of different types (bag fibres and chain fibres) and these are known to have different mechanical properties. Inputs to the muscle spindle are through two types of fusimotor axon. Neural activity in these fusimotor axons is known to alter the

response of the intrafusal fibres to length changes. Outputs from the muscle spindle, which are transmitted back to the spinal cord, are through two different types of axon (the primary (Ia) and secondary (II) afferent axons). Measures of neural activity in these axons provide muscle spindle model outputs.

One of the inherent difficulties is the fact that the muscle spindle is a multi-input, multi-output system of considerable complexity which involves an unusual combination of continuous and discrete variables. Activity in the axons leading to and from the intrafusal fibres takes the form of sequences of identically shaped pulses (action potentials), with the information content of the signals being coded through the instantaneous frequency of these pulse trains. The fusimotor axons from the spinal cord are of two types, termed static gamma axons (γ_s) and dynamic gamma axons (γ_d). Activity in these fusimotor axons alters the response of the Ia and II axons to imposed length changes. These fusimotor signals thus form two inputs to the muscle spindle, along with the length change variable which is a third input variable.

One continuing problem that has an important bearing on the possible role of muscle spindles within the neuromuscular control system concerns the responsiveness of the Ia and II axons to muscle length changes in the presence of fusimotor inputs. Several possible mechanisms have been suggested, including changes in the mechanical properties of the intrafusal fibres following fusimotor stimulation.

Attempts to model the muscle spindle have involved two distinct approaches. In one case available knowledge about the mechanical properties of the different types of intrafusal fibre and the processes that lead to the generation of action potentials in the Ia and II afferent axons has been used to produce detailed theoretical models (e.g. the publications of (Angers & Delisle, 1971) and (Rudjord, 1972) which provide interesting illustrations of early developments of this kind). On the other hand, for many years experimentalists have been applying techniques from linear system theory to obtain transfer function descriptions from experimental test data (e.g., (Poppele & Bowman, 1970); (Hasan & Houk, 1975)).

In the work described in the papers included in this thesis two distinctly different approaches have been investigated in an attempt to apply system identification and parameter estimation techniques to the combined muscle and muscle spindle system to throw light on the problems of muscle spindle behaviour. The first approach considered used classical identification techniques to determine a transfer function between mechanical inputs, such as length changes applied to the muscle, and neural outputs from the Ia and II axons represented by equivalent continuous signals based on instantaneous frequency measures. The intensity of fusimotor stimulation was also represented, through use of the instantaneous frequency measure. The second type of approach put more emphasis on the multi-input multi-output nature of the muscle spindle and involved fewer implicit assumptions about the role of the muscle spindle within the neuromuscular control system. It involved the application of system identification methods to point processes so that useful information could be extracted from tests involving random test signals applied to both the continuous and discrete inputs.

One example of the first type of approach is the work by (Maclaine, McWilliam et al., 1977 - **submitted paper, [1]**), where experimentally- derived linear models,

identified by the maximum-likelihood approach of Åström and Bohlin (1966), were used to investigate interactions between the fusimotor and mechanical inputs to the muscle spindle. The results obtained by this identification method provided a basis for further analysis and interpretation in terms of the mechanical properties of the intrafusal fibres (Maclaine, McWilliam et al., 1977 - **submitted paper, [1]**).

The second method of approach required some preliminary theoretical work before the developments by Brillinger's group at the University of California, Berkeley, on the identification of point-process systems could be applied to the results of neurophysiological experiments. This allowed spectral estimation procedures, based upon the finite Fourier transform and the smoothed periodogram, to be used for the identification of linear point-process models to describe the relationship between a fusimotor input to a muscle spindle and the Ia and II responses. Results were expressed in terms of estimated gain, phase and coherence as a function of frequency (Murray-Smith, Rosenberg et al., 1985 – *supporting paper, [17]*). A range of frequencies can be found over which values of coherence are above an approximate 95% confidence interval under the assumption that the two processes are independent. This may be taken as the range of frequencies over which the linear model may be assumed valid. Estimates for the 95% confidence intervals for the gain and phase can also be found and, over the range of frequencies for which the linear model is assumed valid, the confidence intervals for the gain and phase are found to broaden as the coherence falls.

Applications of these point-process models include investigation of phenomena involving "driving" in which the application of a periodic spike train stimulus, through the fusimotor inputs, produces an afferent spike train which has a pulse frequency directly related to the input train. This phenomenon was also the topic of an earlier investigation using other methods of analysis (Dutia, Murray-Smith et al., 1977 – *supporting paper, [18]*). The range of pulse frequencies over which one-to-one driving occurs in simple nonlinear muscle spindle models has been investigated through simulations and the model parameters which affect the ability of the model to exhibit driving have been found. Adjustment of these parameters has allowed the nonlinear simulation model to provide one-to-one driving over a frequency range that is very similar to that found in experiments (Halliday, Murray-Smith & Rosenberg, 1992 – **submitted paper, [3]**) (Murray-Smith, Rosenberg et al., 1985 – *supporting paper, [17]*).

2.4.2 Modelling of active skeletal muscle

The modelling of muscle has traditionally been carried out on the basis of physiological understanding of the processes of muscle contraction, either at a microscopic or at a macroscopic level. Although the resulting models have the advantage that they involve parameters that have physiological significance these approaches lead to models that are complex and computationally expensive. In most cases they also fail to account fully for some well known nonlinear characteristics of muscle that are observed in experiments. For example, muscle characteristics vary significantly with stimulation frequency and, although models of this type have been developed that allow variation of motoneurone inter-pulse interval (e.g. (Murray-Smith, 1994 -.*supporting paper, [19]*)), the force developed by active muscle depends in a dynamic fashion on the history of the stimulation frequency. The nonlinear

summation of contractions for stimulation pulses involving very short inter-pulse intervals presents a challenge in terms of modelling. The phrase “catch-like effect” is used to describe a particular phenomenon that is observed when a doublet or triplet of pulses with very short inter pulse intervals is applied.

Donaldson *et al.* (1995) successfully used a radial basis function network for modelling isometric contraction of muscle stimulated using pulse trains of varying frequency. This type of approach was used again by Gollee and Hunt (1997) using second order linear models to describe local descriptions of muscle. Second-order linear local models were blended together using a form of scheduler which could select the models closest to a given operating point and interpolate between models. The blended structure then forms a time varying description of the muscle. The model developed by Gollee and Hunt (1997) was, however, limited to muscle having a majority of fast motor units and was not applicable for other types of muscle.

The work of (Gollee, Murray-Smith and Jarvis, 2001 – **submitted paper, [20]**) represents an attempt to extend and generalise the work of Gollee and Hunt (1997). The approach used involved dividing the complex task of modelling active skeletal muscle into smaller and simpler sub-tasks. Each of those sub-tasks could then provide the basis of a sub-model, valid locally, and a scheduler provided a way of establishing the relevance of the different sub-models for the current operating condition and weighted the contributions of those sub-models accordingly. The complete model was formed of the sum of all the weighted local models.

The local models which form the sub-models within the system model can be of any linear or nonlinear form and may be based on *a priori* knowledge of the corresponding real system. In the case of the muscle modelling work local linear sub-models were applied. Linear models of second order were used, with an added pure time delay. The scheduling variable was based on a measurement of the instantaneous stimulation frequency and this was found to work well with both fast and slow muscle.

The experimental procedure involved system identification. Tests were used for the estimation of parameters of the local model network and for each model this involved 30 data sets. The remaining test data sets (involving at least 30 sets) were then used for validation purposes. The procedure for identification involved starting with a single linear model and steadily increasing the number of units in the network. Although the error on the training data sets tended to decrease with the number of LMN units the error for the test data sets was found to rise once the optimum model size had been reached. The structure with the smallest value of test error was chosen as the optimal structure.

Results from these experiments showed that, for fast muscle, six local models corresponded to the optimum while, for slow muscle, five sub-models were adequate. With both types of muscle an excellent match could be achieved and the “catch-like” effect was accurately represented. Although it is recognised that local model network methods have important limitations and that conclusions drawn from the behaviour of a local identified model must be treated with caution, it is clear from this study that the approach does provide a potentially useful method for the experimentally-based modelling of electrically stimulated skeletal muscle under isometric conditions. This

work on identification of muscle through the use of local model networks formed part of a broader study concerned with the use of electrically stimulated skeletal muscle for cardiac assist situations (Jarvis, Gollee et al, 1996 – *supporting paper, [21]*). Further work is necessary in order to be able to investigate the possible benefits of the local model network approach for the modelling of skeletal muscle for other experimental conditions.

2.5 Applications in Helicopter Flight Mechanics Modelling

The application of system identification and parameter estimation techniques to problems of helicopter flight mechanics modelling and control is of considerable practical importance, especially for flight test validation of predictive models developed on the basis of physical laws and principles. However, helicopters and other forms of rotorcraft present a number of problems in terms of system identification. In the identification of linearised multi-input multi-output models of the dynamics of the complete vehicle it is normal to be faced with test records that are short in relation to the dominant dynamic characteristics of the system. Nevertheless, these models involve many parameters and a wide range of frequencies, in addition to high levels of noise. This is a combination of factors that is generally considered undesirable for the successful application of system identification and parameter estimation methods.

From the viewpoint of the helicopter industry the benefits of helicopter system identification relate to the potential to reduce the amount of flight testing that has to be carried out in the context of certification of new designs and to achieve improvements in agility and handling qualities through fine tuning of flight control systems. The costly and time-consuming flight testing programmes for new helicopter designs, while being concerned principally with certification issues, are also aimed at improving the confidence in underlying physically-based models used in design and in reducing the level of uncertainties in these models. Estimation of parameters from flight tests is increasingly seen as an important part of such testing and is especially relevant in the context of important aerodynamic stability and control parameters

Another factor, which provided a further stimulus to those engaged in the application of system identification methods to helicopters and other forms of rotorcraft in the late 1980s and 1990s, related to the implementation of active control technology concepts in rotorcraft. Essentially, this is the fly-by-wire approach that had, by then, already been accepted in fixed-wing aircraft. The improvements in performance and operational capabilities expected from the introduction of active-control technology could only be achieved through the availability of accurate and proven mathematical models (Murray-Smith, 1995 - *supporting paper, [22]*) The publication in 1989 and in 1994, in the USA, of revised handling qualities requirements for military helicopters (Anonymous, 1994) provided a stimulus to flight control system design and created new interest in the potential and practical limitations of multivariable control system analysis and design methods. Enhanced performance requirements and developments in materials and rotor technology have led to major improvements in vehicle characteristics which mean that much enhanced performance is possible and traditional loop-by-loop design methods are no longer adequate. Multivariable control system design techniques, which more fully exploit the inherently multivariable

structure of these vehicles, have been applied in a number of investigations (e.g., (Manness & Murray-Smith, 1992 – *supporting paper, [23]*), (Gribble, Manness & Murray-Smith, 1994 – *supporting paper, [24]*), (Gribble & Murray-Smith, 1990 – *supporting paper, [25]*), (Hughes, Manness & Murray-Smith, 1990 – *supporting paper, [26]*), (Manness, Gribble & Murray-Smith, 1990 – *supporting paper, [27]*)). However, ensuring an appropriate level of accuracy in the multi-input multi-output models used for active control system design is a major challenge. Models are required that perform adequately over a defined range of frequencies and over a specific range of manoeuvre amplitudes.Improved models undoubtedly offer direct benefits in terms of performance. For example, high-bandwidth model-following flight control systems based on accurate mathematical models may incorporate improved feed-forward control pathways and allow improved agility and some reduction of high feedback gain values that would otherwise have to be introduced to compensate for model deficiencies.

System identification methods are also becoming increasingly important in the context of validation of ground-based simulators for rotorcraft of all types. Such simulators require highly accurate mathematical models if they are to be useful for pilot training (see, for example, (Hamel, 1994)).

2.5.1 Identification methods for rotorcraft applications

Prior to the 1990s most published accounts of applications of system identification techniques to helicopters and other types of rotorcraft involved time-domain methods of identification. Another approach, which is believed to have advantages, involves the use of frequency-domain methods. In this case the measured response data are transformed first into the frequency domain using an appropriate implementation of the Fast Fourier Transformation. This allows attention to be focused on a particular part of the frequency range and data lying outside the range of interest can be discarded or given less emphasis. This means that, for the identification of six-degrees-of-freedom rigid body models, the rotor degrees of freedom, which involve higher frequencies can be excluded. Conversely, for the identification of rotor dynamics, the exclusion of lower frequencies involving the rigid-body response can be advantageous. This procedure allows, in a sense, a form of model reduction within the identification process (Padfield, Thorne et al., 1987 – *supporting paper, [28]*). Details of a frequency-domain approach to helicopter system identification developed during the period 1984-1988 may be found in a paper by Black and Murray-Smith (Black & Murray-Smith, 1989 – **submitted paper, [29]**). This approach was one of a number of methods of helicopter system identification successfully used by the NATO-supported AGARD Flight Mechanics Panel Working Group WG18 in the preparation of the AGARD Advisory Report 280 (Anonymous, 1991) on Rotorcraft System Identification. Frequency-domain methods have become increasingly widely used in the years since publication of that AGARD report, especially with the now widely available CIFER software developed by Dr Mark Tischler and his colleagues at the US Army Aeroflightdynamics Directorate (Tischler & Remple, 2006).

In the system identification approach developed by Black and Murray-Smith, the selection of the model structure and the estimation of parameters involved a three-stage approach. This is based on initial use of frequency-domain equation error techniques, followed by further refinements of estimates through the use of output-error techniques and then a final time-domain output error procedure. Work was

carried out using single records for a number of simultaneously recorded variables and also combinations of records. The analysis of combinations of records involved the application of a technique for multiple-run identification which retains the individuality of separate runs and avoids some of the problems resulting from simple concatenation of files (Leith, Bradley & Murray-Smith, 1993 – **submitted paper, [30]**). This multiple-cost approach involves the introduction of an additional summation loop involving the individual cost functions for each of the separate data sets. This gives, for *N* data sets, a combined cost function

$$J_{TOTAL} = \sum_{i=1}^{N} J_i \tag{2.7}$$

Analysis has also shown that, for appropriate conditions, estimates of multiple-run parameter values and their standard deviations may be obtained from the individual results obtained from the runs that form the basis of the multiple-run identification. This means that conventional single-run system identification techniques and software can be used without alteration for multiple cost identification. The paper includes an illustrative example, with excellent results, involving the application of the multiple-cost identification approach to flight data from a Puma helicopter.

The individual cost functions used in the frequency-domain output-error stage of the three-stage identification procedure described in the paper by Black and Murray-Smith (1989) are based on use of the maximum-likelihood approach and involved summation over a specified range of frequencies. A feature of this approach to state-space system identification is the use of pseudo-control inputs and some parameters were fixed during the identification process. Within each iterative cycle the error-covariance matrix estimate is updated using predicted model outputs. Minimisation of the cost function involved use of a quasi-Newton method together with an optimal linear search algorithm. In this output-error approach, convergence is necessary in both the model parameter values and in diagonal elements of the error-covariance matrix. The frequency-domain output-error identification process is followed by a time-domain output-error identification stage in order to estimate zero offsets and initial states which require information not included in the frequency-domain data.

Although it may be stated, without question, that system identification and parameter estimation techniques are potentially very important in the context of helicopter development and flight testing, it has to be accepted that the benefit of these tools has not yet been fully realised. Many of the difficulties are associated with issues of robustness and these have been classified under the following headings (Murray-Smith, 1991c – *supporting paper [31]*):

1. robustness and reliability of *a priori* information,
2. robustness of the identified model structure,
3. robustness of estimated parameters,
4. robustness of the resulting overall model.

In the context of these robustness issues the properties of different estimators are likely to be less important than questions of identifiability, the quality of measured system response data and experimental design (Murray-Smith, 1991c – *supporting paper, [31]*), (Leith & Murray-Smith, 1989 –**submitted paper, [32]**), (Leith, 1994).

2.5.2 Test inputs for helicopter system identification and parameter estimation

Test inputs commonly used for helicopter system identification include doublet signals, other forms of multi-step signals such as the so-called "3-2-1-1" pseudo-stochastic signal (Plaetschke & Schulz, 1979, Kaletka, 1979) and frequency-sweep signals. The coherence function has been found to be a valuable measure of the degree to which a given type of signal provides satisfactory excitation in helicopter system identification (Tischler, 1987). This quantity provides a measure of the fraction of the output auto-spectrum which may be accounted for by a linear relationship with the input auto-spectrum. In the ideal case the coherence is unity over the complete frequency range of interest. Values of coherency smaller than one may be associated with nonlinearity in the system under test, process noise (such as turbulence in the case of aircraft applications) or lack of input signal power and thus response power (Bendat & Pearsol, 1980), (Bendat & Pearsol, 2000).

Designs of test signals for practical system identification of a helicopter or any other air vehicle are inevitably based on a mathematical model of that vehicle. Because of uncertainties within that model they are unlikely to be optimal. Indeed, if uncertainties were not present there would be no need for system identification testing. This means that it is important to characterise some appropriate flight data from the vehicle in question as a first step towards experimental design. This is essentially the same procedure as was applied in the development of improved forms of test signal for investigation of the pulmonary gas exchange model in Section 2.3.

As with the work on test input design for physiological systems, it is essential to have a quantitative basis upon which test signals can be compared. In the work outlined here this involved the use of quantities such as the parameter information matrix and the dispersion matrix, both of which have theoretical origins in the Cramer-Rao bound (Plaetschke & Shulz, 1979). This has led to test input design algorithms that minimise some appropriate function of the dispersion matrix or of the parameter information matrix, as outlined in Section 2.2. It should be noted, however, that care must be taken when applying such an approach due to the fact that, unless an efficient estimator is used, the approach may be invalid and the resulting designs cannot be relied upon. Inputs designed using measures based on the dispersion matrix are useful in cases where long test records are available and where maximum-likelihood estimators are being applied since such estimators are asymptotically efficient.

2.5.3 Experimental design for linearised six-degrees-of-freedom helicopter models

In cases where the purpose of the identification is concerned with validation of linearised flight mechanics models, the inputs that are being used for testing must be consistent with the modelling assumptions. This means that input design methods must take account of any input constraints that may exist. In addition, it is important to obtain long test records since parameter estimates then have time to converge and efficient (i.e. minimum variance) estimation is possible, thus allowing use of dispersion matrix criteria in the design process.

The broad aim of research by (Leith & Murray-Smith, 1989 **– submitted paper, [32]**) was to design a test input which would give long test records while providing

providing a dispersion matrix that is reasonably "small". Avoiding resonances in the system is an important requirement since an input that excites these resonances would produce a response that would rapidly become nonlinear and this might require the flight experiment to be prematurely aborted. Inputs should also be such that there is no steady state component in the signal. For many cases of practical importance a constant component in the test input will produce a steady-state constant component in the response and this tends to shift the operating condition of the aircraft. If the operating point is significantly different from the operating point used for linearisation of the theoretical model the parameter estimates obtained experimentally will be inconsistent with that model, thus making the whole procedure invalid.

The paper by (Leith & Murray-Smith, 1989 **– submitted paper, [32]**) presents a method of autospectrum design that:
a) ensures that resonances are avoided, to give longer test records.
b) avoids exciting frequencies around the resonances, to give robustness
c) excites the remaining frequencies to give a reasonably "small" dispersion matrix.
A further requirement is that inputs have to be relatively simple in form so that they can be applied manually by the pilot.

An optimal spectrum program was developed successfully to produce a binary multi-step input having an auto-spectrum that satisfies a specification of the type outlined above.

The starting point for the development of the optimal spectrum program was to consider a general a-periodic binary multi-step input which could be described in terms of its Fourier transform by :

$$F(\omega) = \frac{1}{j\omega}\left[1 + 2\sum_{i=1}^{n-1}(-1)^i \exp(-j\omega t_i) + (-1)^n \exp(-j\omega t_n)\right] \tag{2.8}$$

where $F(\omega)$ is the Fourier transform of the signal, ω is the frequency (rad/sec), n+1 is the number of steps in the binary input sequence, t_i is the time in seconds of the ith step in the input and $t_0 = 0$ sec.

The cost function is defined as

$$I = \sum_{k=1}^{m} a_k \left|F(\omega_k)\right|^2 \tag{2.9}$$

and the optimal spectrum program uses as input the number of steps n in the input sequence, the number, m, of weighting factors in the cost function I and the values of the frequencies ω_k and the corresponding weighting factors a_k . These last two are chosen so that the requirements are satisfied in terms of frequencies that should and should not be excited. For a given value of n the cost function has to be optimised in terms of the timing of the fixed number of steps in the multi-step input. The specification of a large positive value of a_k produces an input having a small component of the auto-spectrum at frequency ω_k, while specification of a large negative value gives an auto-spectrum with a small magnitude at that frequency.

This approach was applied successfully to the design of test inputs for a Lynx helicopter operating at RAE (Bedford). Flight trials were performed for a test input applied to the longitudinal cyclic control of the vehicle for a flight condition of 80 knots level flight. As described in (Leith & Murray-Smith, 1989 – **submitted paper, [32]**), the optimal test signal design process was carried out with weightings chosen to ensure that the input auto-spectrum had no dc component, that it avoided known resonances at about 0.3 rad/sec and that the input excited frequencies between 2 and 3 rad/sec but not above 3 rad/sec. The upper limit of 3 rad/sec was imposed because previous experience at RAE (Bedford) suggested that the theoretical model was useful only for frequencies below about 3 rad/sec. At higher frequencies it appears that dynamic effects within the rotor sub-system have a significant influence and these were not included in the model. A signal consisting of five steps was found to be particularly useful. This signal, a double-doublet, allowed long test records before the response became nonlinear. Typical record lengths for the double doublet with the Lynx helicopter were of the order of 30 seconds compared with 10-15 seconds for a traditional doublet input and only 3 seconds for the 3-2-1-1 input. Estimates of seven parameters of the pitching moment equation were obtained using the frequency-domain equation-error approach described in (Black & Murray-Smith, 1989 – **submitted paper, [29]**). Other forms of multi-step input were considered and tested in flight but the double-doublet gave results that were consistently better than those obtained from the use of other inputs. The double doublet appears to be more robust to errors and uncertainties in the theoretical model used in its design.

It is of interest to note that the techniques adopted for the design of test signals for the rotorcraft application differ from those applied in modelling the gas exchanging properties of the lungs. In that application the test signals were designed to minimise an appropriate function of the dispersion matrix, such as the determinant, in the time-domain. In this application frequency-domain methods were adopted, partly because of the physical insight that these provide in the subsequent application of the models for flight control system design and also the fact that the frequency domain offers the possibility of separating six-degrees-of-freedom dynamics and rotor dynamics.

A further paper (Leith & Murray-Smith, 1993 – *supporting paper, [33]*) - discusses the development of energy and amplitude constrained optimal inputs for use in system identification. Although that paper includes a study based on a fifth-order helicopter flight mechanics model as an example, the paper is written in a more general way and the results could be applied to any problem involving a combined input and state energy constraint or an output amplitude constraint. For these types of constraint the design of D-optimal inputs is first demonstrated for a simple first-order system and the insight provided by this approach is emphasised. The fifth-order helicopter example involves an output amplitude constraint. Although the best result was obtained using the output amplitude constrained test input, this example provides further evidence of the advantages of the double-doublet design over other conventional test signals such as the doublet.

Further discussion of flight test procedures, design of experiments and robustness issues in helicopter system identification may be found in (Murray-Smith, 1991a – *supporting paper, [34]*), (Murray-Smith & Padfield, 1991 – *supporting paper, [35]*) and (Murray-Smith, 1991b – *supporting paper, [36]*). Further discussion of results from the application of system identification methods to helicopter flight mechanics

model development are presented in (Padfield & Murray-Smith, 1991 – *supporting paper, [37]*).

2.5.4 System identification strategies for helicopter rotor models

Coupled models describing rotor flapping dynamics and rotor inflow phenomena are of great importance in helicopter flight mechanics and for the design of flight control systems. The system identification technique developed by (Black & Murray-Smith, 1989 – **submitted paper, [29]**) which involves a combination of equation-error and output error methods in the frequency domain, is well-suited to the investigation of rotor models although it was developed initially for the identification of rigid body helicopter models. The main advantage of this method of approach is that it provides a way of partially decoupling the estimation of parameters of a rotor model, involving relatively high frequencies, from the estimation of parameters within the rigid-body six-degrees-of freedom description which involves the low-frequency part of the spectrum.

The application of system identification methods to models of the main rotor in a vehicle having a conventional single main rotor and tail rotor helicopter configuration is challenging because of difficulties in exciting the rotor blades over a wide enough range of frequencies and also because of the inherent problems of measuring the air flow though the rotor. A paper by (Bradley, Black & Murray-Smith, 1989 – **submitted paper, [38]**) describes the application of the frequency-domain approach to the estimation of parameters within four competing theoretical models incorporating induced flow. The most general form of model considered involved a second-order description with induced-flow dynamics, which could be reduced to a first-order description with induced-flow dynamics or to either a first or second order form without induced flow dynamics. A modified form of state equation:

$$\boldsymbol{E}\dot{\boldsymbol{x}} = \boldsymbol{A}\boldsymbol{x} + \boldsymbol{B}\boldsymbol{u} \tag{2.10}$$

was adopted because it was found that use of this form of mathematical description could facilitate direct estimation of physically meaningful parameters. With this representation defined relationships can exist between the elements of the $\boldsymbol{A}$, $\boldsymbol{B}$ and $\boldsymbol{E}$ matrices.

Conclusions from this work indicated that the time constant of the dynamics of the induced flow is of the same order as that of the dynamics of tilting of the rotor disc for the flight condition considered. The formulation of the equations using the structure of Equation (2.10) was found to be a particularly useful development because it facilitated physical interpretation of results and released investigators from the restrictions of the standard state-space formulation.

2.6 Discussion

One important feature of the papers included in the thesis is that they discuss modelling and control applications from a variety of areas, including physiology, electro-optics and rotorcraft dynamics as well as more traditional control engineering areas such as ships, underwater vehicles and electrical power generation systems. The objectives of modelling in these different areas can differ significantly and prior knowledge of the real system can be very important. It is also essential to have a full understanding of how the model is to be used. The purpose of a model influences the type of model needed and, if the goal is to provide further insight about the corresponding real system, the form of the model may be significantly different from models used for quantitative prediction, simulation or control system design.

The benefits of a cross-disciplinary approach to system modelling are believed to be very significant and the value in terms of cross-fertilisation of ideas resulting from involvement in a wide range of applications can be seen from the detailed content of the papers. Although the fields of neurophysiology, respiratory gas exchange processes, electro-optic sensor-systems, helicopter flight mechanics, hydro-electric power generation and surface ship or underwater vehicle control appear to have little in common, closer examination shows that systems from these different fields present many similar difficulties in terms of accurate modelling. The papers included here show that, in addition to displaying significant nonlinear behaviour, most credible models of such systems involve significant uncertainties in the early stages of their development. Significant simplifications may also have to be introduced, often for reasons of computational complexity, if the model is to be useful for an application such as non-invasive measurement, a real-time system simulator or the design of an automatic control system.

System identification and parameter estimation techniques are important tools for the modelling of complex systems. The papers included in this section of the thesis focus on practical aspects of system identification and three very different fields of application are considered, two involving biological systems and one involving a complex engineering system. Similarities highlighted by the research reported in these different application areas include problems of inherent system complexity, difficulties caused by having to work with short data records and complications introduced by experimental constraints, poor signal to noise ratios and nonlinearities.

When used as a tool for refinement of system models, or for the indirect estimation of physical quantities which are not accessible to direct measurement, system identification methods are needed which provide a clear indication to the user of the accuracy of parameter estimates and of the validity of the model structure. In parametric models, questions of accuracy can be closely linked to issues of numerical identifiability and thus to experimental design. However, in many cases, especially with nonlinear parametric models establishing the accuracy of estimated quantities is not straightforward (see, for example, (Nelles, (2001), pp. 431-434)). In the case of non-parametric models useful insight concerning the range of validity of estimates can be gained from the use of measures such as coherence.

Following the successful application of identification methods, simulation tools can be used in the evaluation of the resulting models and for the assessment of competing

hypotheses in cases where major uncertainties remain. Such an approach can lead to the formulation of new experiments and to a further stage of model refinement if that is necessary for the intended application.

3. Inverse Simulation for System Modelling

3.1 Introduction

Inverse simulation techniques applied to linear or nonlinear dynamic models allow the determination of time histories of system "inputs" needed to achieve a specified time history for a given set of required "outputs". This approach has attracted considerable attention in the field of helicopter flight mechanics and a number of methods of inverse simulation have been in use within the helicopter research community since the late 1980s and early 1990s. The techniques are of potential interest for other types of application as they provide important insight about requirements in terms of the actuator characteristics needed to achieve given levels of controlled output performance. This is especially important when constraints, such as amplitude and rate limits, are present and the approach is potentially useful for a wide range of mechatronic and control systems applications, including integrated control systems.

The first techniques, developed mainly for aircraft applications, may be divided into three categories: (a) differentiation methods as developed by Kato and Saguira (1986) and by Thomson and Bradley at the University of Glasgow (e.g., (Thomson & Bradley, 1990); (Thomson & Bradley, 1994), (b) integration methods which originated with the work of Hess and his colleagues at the University of California, Davis (e.g., (Hess, Gao & Wang, 1991) and, independently, by Thomson and other members of his group at the University of Glasgow (e.g., (Rutherford & Thomson, 1996) and (c) methods which adapt traditional numerical optimisation algorithms for use in inverse simulation (e.g., (de Matteis, de Socio & Leonessa, 1995), (Lee & Kim, 1997) and (Celi, 2000).

The mathematical basis of inverse simulation and the differentiation and integration based methods, which are based on the Newton-Raphson (NR) algorithm, are described in a review paper published in discussing inverse simulation methods and their applications (Murray-Smith, 2000b - *supporting paper, [39]*). The integration-based approach using the NR algorithm is the most widely used technique at present.

Known difficulties with the integration-based method involving use of the NR algorithm include:

- the existence of oscillations in the calculated inputs which are of high frequency compared with the dynamics of the system being simulated;
- possible non-convergence of the algorithm;
- the occurrence of maintained or slightly damped oscillations (so-called *constraint oscillations*) of frequency similar to the frequency of an oscillatory mode of the system;
- numerical issues associated with the use of derivative information in the calculation of the Jacobian.

More fundamental issues that also apply to other techniques are concerned with the structure of the model. One important limitation is that redundancy issues when the number of system inputs is greater than the number of outputs may lead to non-

convergence of inverse solutions. Another issue is that the stability of inverse simulation techniques for the case of non-minimum phase systems has been given little attention in the past.

It should be noted that inverse simulation techniques differ significantly from the techniques of dynamic inversion which were developed by Brockett (1965), Dorato (1969) and Hirschorn (1979) and further developed by Isidori and his co-workers (e.g., (Isidori, (1995)). Dynamic inversion involves transformation of the original nonlinear system model into a linear and controllable model using a nonlinear state feedback control law using concepts from differential geometry. Surprisingly little consideration has been given in most published work to the relationship between model inversion and inverse simulation techniques.

Although there have been a number of useful review papers describing the principles and practical application of inverse simulation methods to problems of flight dynamics, including two very useful reviews by Thomson and Bradley (1998) and (2006) and a more general review paper by (Murray-Smith, 2000b – *supporting paper, [39]*), little progress appeared to have been made by the start of the twenty-first century with the application of the inverse simulation approach to problems in other application areas. The approach also appeared, at that time, to have attracted no attention as a possible alternative to analytical methods of dynamic inversion for control system design. These areas of work, together with developments aimed at eliminating some of the current difficulties with inverse simulation algorithms, have been emphasised within the papers on inverse simulation that are included in this thesis.

3.2 Developments in Inverse Simulation Methods

3.2.1 An inverse sensitivity approach

The paper published in 2007 by (Lu, Murray-Smith & Thomson, 2007- **submitted paper, [40])** discusses numerical problems encountered with traditional methods of inverse simulation based on the NR algorithm and proposes a new method of inverse simulation based on sensitivity analysis theory. This new technique has been termed "inverse sensitivity". The central idea in this approach is that the system input vector can be regarded as a vector of time-varying parameters α which are independent of the state variables. In the traditional inverse simulation algorithm the input vector is assumed constant within the small time interval $t_k < t \leq t_{k+1}$ and it follows that the vector $\alpha(t)$ is a constant vector over that interval. This means that within the interval $t_k < t \leq t_{k+1}$ the standard state space form of description for a nonlinear system can be expressed in the form:

$$\dot{\boldsymbol{x}} = \boldsymbol{f}(\boldsymbol{x}, \alpha) \tag{3.1}$$

$$\boldsymbol{y} = \boldsymbol{g}(\boldsymbol{x}, \alpha) \tag{3.2}$$

Transforming these equations into sensitivity equation form, as shown in (Lu, Murray-Smith & Thomson, 2007- **submitted paper, [40])**, leads to a set of equations in the form:

$$\dot{\boldsymbol{V}} = \boldsymbol{A}(t)\boldsymbol{V} + \boldsymbol{B}(t)$$
$$\boldsymbol{H} = \boldsymbol{C}(t)\boldsymbol{V} + \boldsymbol{D}(t) \tag{3.3}$$

where

$$\boldsymbol{V} = \frac{\partial \boldsymbol{x}}{\partial \boldsymbol{\alpha}^{\boldsymbol{T}}}; \quad \boldsymbol{A}(t) = \frac{\partial \boldsymbol{f}}{\partial \boldsymbol{x}^{\boldsymbol{T}}}; \quad \boldsymbol{B} = \frac{\partial \boldsymbol{f}}{\partial \boldsymbol{\alpha}^{\boldsymbol{T}}}; \quad \boldsymbol{H} = \frac{\partial \boldsymbol{y}}{\partial \boldsymbol{\alpha}^{\boldsymbol{T}}}; \quad \boldsymbol{C} = \frac{\partial \boldsymbol{g}}{\partial \boldsymbol{x}^{\boldsymbol{T}}} \quad \text{and} \quad \boldsymbol{D} = \frac{\partial \boldsymbol{g}}{\partial \boldsymbol{\alpha}^{\boldsymbol{T}}}$$

Equations (3.3) are the continuous sensitivity equations which allow the system output sensitivity functions to be calculated through forward simulation. It can then be shown that a small perturbation in the vector $\boldsymbol{\alpha}$ at time t_k results in an output variation $\Delta \boldsymbol{y}_{\boldsymbol{k+1}}$ and the inverse simulation problem becomes an inverse problem for finding the value of $\Delta \boldsymbol{\alpha}_k$ from an equation of the form:

$$\Delta \boldsymbol{y}_{\boldsymbol{k+1}} = \boldsymbol{\Gamma}(\Delta \boldsymbol{\alpha}_k) \tag{3.4}$$

Full details concerning solution of this equation are provided in the paper (Lu, Murray-Smith & Thomson, 2007 - **submitted paper, [40])**. The benefit of this approach is that it allows the Jacobian matrix to be obtained through simulation rather than by means of the usual approximation based on numerical differentiation and thus avoids many of the problems associated with that process. The disadvantage lies in the computational demands of this method since the order of the sensitivity equations is *q* times larger than the order of the original state equations, where *q* is the order of the input vector. There is thus a need to balance the improved accuracy against the increase in computational requirements.

Certain basic rules for convergence and stability apply to the inverse sensitivity solution and numerical examples included in the paper show that inverse simulations based on the sensitivity analysis method can provide the same results as the traditional method based on the NR algorithm. However, detailed analysis shows that for a given time interval $\Delta t = t_{k+1} - t_k$ results from the sensitivity approach can be approximately four times more accurate than results from the traditional NR approach. As the number *M* of Runge-Kutta integration steps within the interval Δt is varied an accuracy improvement is found for the SA method up to a value of about M=20. No corresponding improvement is found in the results for the NR algorithm. Beyond M=20 in the SA method there can be further accuracy improvements but these are less marked and involve considerable computational cost. There is a clear trade-off between accuracy and computer time in the choice of *M* for the SA method and a large value of *M* is preferred but is not essential. In addition these results mean that it is not essential to use a small Δt value in the application of the SA method. Thus, in some cases the problems associated with small Δt values in the NR method that lead to high frequency oscillations can be avoided.

3.2.2 The constrained Nelder-Mead method

The established methods of inverse simulation, through the differentiation and integration-based approaches, introduce additional derivative information associated

with calculation of the Jacobian or Hessian matrices. Direct search methods of optimisation are derivative free and thus avoid issues that may arise in gradient based methods when discontinuities are encountered, such as input saturation.

The 2008 paper by (Lu, Murray-Smith & Thomson, 2008 – **submitted paper, [41]**) provides details of a novel derivative-free approach to inverse simulation based on a version of the downhill simplex optimisation method of Nelder and Mead (1965). The Nelder-Mead (NM) approach is a widely used method for minimising a scalar-valued nonlinear function of real variables, using only function values without any explicit or implicit gradient information. Recent developments in the method allow it to be applied to multimodal, discontinuous and constrained optimisation problems. The algorithm used as the basis for development of the derivative-free inverse simulation method is based on the version of the Nelder-Mead algorithm by Lagarias et al. (1998) with an additional feature to allow for input-constrained functions.

As with the integration-based method using the NR algorithm, the NM approach involves consideration of an interval $[t_k, t_{k+1}]$. A key feature of the method is that the optimisation is based upon a cost function and the choice of this function is of critical importance.

The paper by (Lu, Murray-Smith & Thomson, 2008 - **submitted paper, [41]**) discusses numerical issues and stability of inverse simulation with the integration-based NR iterative scheme, including the constraint oscillation phenomenon and problems associated with input saturation and discontinuities. The same issues are also discussed in the context of the constrained NM method, outlined above, and two case studies are used to compare the use of the NM method with the more conventional NR approach. These investigations both involve nonlinear mathematical models used in ship steering control.

The first of these case studies involved a relatively simple nonlinear model of the Norrbin type, which is a single-input single-output description. The model includes rudder amplitude and rate limiting. Although results from inverse simulations by the two approaches agree well with each other for ship manoeuvres that involve rudder angles and rates that are below the limits, it has been found that the NM-based approach can achieve good convergence and provides physically meaningful inverse simulation results in cases where the NR algorithm fails to converge.

The second case study involved a nonlinear container ship model which has two inputs and three output variables. In this example turning circle and pullout manoeuvres were considered and good convergence was achieved for both the NR and NM methods with and without input saturation for the turning circle manoeuvre. However, in the case of the pullout manoeuvre, the NM method was successful but the NR algorithm failed to converge for any of the cases considered due to the discontinuity in the manoeuvre.

It is concluded from the results of these case studies that the derivative-free procedure based on the constrained NM algorithm provides important benefits compared with the more conventional approach based on the NR algorithm. The new approach gives improved convergence and numerical stability properties compared with the NR algorithm for cases that include significant input saturation or involve a discontinuous manoeuvre.

3.3 Inverse Simulation Applications in System Modelling

Aeronautical applications considered in the research on inverse simulation methods for system modelling include a relatively simple HS-125 fixed-wing aircraft model having thrust and elevator inputs and a Lynx helicopter model involving five sub-systems: fuselage, tail plane, fin, main rotor and tail rotor (Lu, Murray-Smith & Thomson, 2007 – **submitted paper, [40]**). Surface ship applications are discussed in (Lu, Murray-Smith & Thomson, 2008 - **submitted paper, [41]**), and underwater vehicle applications in (Murray-Smith & Lu, 2008 – **submitted paper, [42]**) and in (Murray-Smith, Lu & McGookin, 2008 - **submitted paper, [43]**).

3.4 Inverse Simulation Techniques for Model Validation

Conventional methods for the external validation of dynamic models generally involve comparisons of the real system with corresponding simulation model responses when both the real system and the model are subjected to the same input for exactly the same operating point. Methods of external validation based on this general approach have been found to be particularly useful in the case of linearised models and for some forms of nonlinear model. However, in the case of models that involve hard limits and other significant nonlinearities (for example, for helicopter flight mechanics models for applications involving manoeuvres, such as nap-of-the-earth flight, that demand large and aggressive control inputs) most traditional methods of validation have been found to have practical limitations. The use of inverse simulation methods and the comparison of inputs needed to achieve a specified form of response can offer insight that can be significantly different from any information derived from more conventional validation methods.

This fact is especially true in the case of systems in which the immediate response to inputs is essentially one of integration. Drift is almost inevitably present in such systems and is due to small biases and offsets. Such offsets are unlikely to be the same in the system and the model and can cause considerable difficulties as they may produce effects having magnitudes that are similar to responses to the applied test input. This issue has been examined in detail in the paper by (Bradley, Padfield et al. 1990 - **submitted paper, [44]**) in the context of helicopter nap-of-the-earth manoeuvres where a strong case is made for the development of a validation strategy that integrates forward and inverse simulation. Other published studies of inverse simulation for model validation applications have included the work of (Murray-Smith & Wong, 1997 – *supporting paper, [45]*), where inverse simulation was applied successfully to a laboratory scale system involving two coupled tanks of liquid. Modelling errors observed in predictions made through conventional forward simulation runs were fully reflected in results from inverse simulation. The difficulty in terms of the model development process is that results from inverse simulation do not allow the deficiencies in the model structure or parameter values to be established directly. The investigation of modelling errors and uncertainties would require further inverse simulation tests based on other measured variables and possibly additional experimentation using conventional forward simulation. One important facility that is lacking at present is an efficient method of sensitivity analysis that would allow discrepancies between inputs predicted by inverse simulation and the inputs applied

experimentally to be related to the structure and parameters of the model under investigation.

3.5 Discussion and Conclusions

Developments in inverse simulation methods that are presented in the thesis include a sensitivity-based technique and the novel application of methods of search-based optimisation. Both these approaches show some interesting advantages over conventional methods of inverse simulation involving gradient techniques. In particular, the new derivative-free approach based on the use of the constrained Nelder-Mead algorithm has been shown to have important advantages for problems involving input constraints, abrupt changes of required output or discontinuities within the model. Simulation studies involving two different nonlinear models of ships which included actuator saturation and rate limit nonlinearities showed that the use of the Nelder-Mead approach could, for cases of this kind, give significantly improved properties in terms of convergence and numerical stability compared with more conventional methods.

Investigations concerned with the traditional approaches to inverse simulation have included studies of numerical accuracy and stability and have provided an explanation of "constraint oscillation" phenomena in terms of internal system properties. In addition, these investigations have focused on the effect of discontinuous manoeuvres, discontinuities within the model and input constraints on instability and convergence failure for integration-based methods of inverse simulation based on the Newton-Raphson algorithm. These investigations have confirmed the superiority of the search-based type of algorithm for applications of this kind.

Inverse simulation methods form an important area for further research, including work on the further development and refinement of inverse simulation algorithms. In their present state of development these techniques are very far from being engineering tools that are suitable for routine use in engineering system design and development. Although the underlying approach has been tested and has proved useful in a number of different application areas, much remains to be done. Even with present day personal computers inverse simulation computations using the well-established Newton-Raphson integration-based approach or the new approaches discussed in this thesis (the inverse sensitivity approach and the Nelder-Mead search-based method) are very time-consuming and also remain somewhat unpredictable in terms of convergence properties. They are therefore inappropriate for routine use in a design environment. Significant effort is needed to develop more efficient and robust inverse simulation tools.

4. Issues of Model Quality and the External Validation of Dynamic Models

4.1 General Issues

For physiological and other scientific applications, the purpose of a model is usually to explain a complex set of behaviours or to help in the design of experiments as part of the process of hypothesis testing. In such fields, model development is a central element of the scientific method. In some engineering applications it may also be appropriate to use a model to describe, analyse or explain the behaviour of a highly complex system but it is much more common to find models being used to assist in decision making or to underpin design activities. A properly tested and well-proven model can reduce engineering system development times and costs significantly for many applications and complex computer-based models provide the basis for much analysis and design.

In all such application areas it is usual to base the structure of the model on prior physical, chemical or biological knowledge but, in many cases, some sub-models may be based purely on input-output descriptions derived from tests carried out on the corresponding elements of the real system (i.e. “black box” models). Models can thus range from completely “transparent” descriptions based on the application of recognised and accepted scientific or engineering principles to purely empirical and thus more opaque “black box” forms. Between these extremes there is a very important class of description, sometimes referred to as a “grey box” model. In such cases some elements of the model are based on empirical descriptions derived using system identification and parameter estimation methods, but much of the model is based on prior knowledge and the application of well-established physical laws and principles.

In industrial applications of modelling and simulation there is much interest in modularisation and component reuse as these are key productivity factors in the software development process. In both industry and the academic world, until recently at least, successive generations of simulation models were often restarted from scratch which is clearly time-consuming and wasteful. Recent advances in object-oriented design and programming methods allow for repositories of reusable objects that can help to reduce the problems associated with the generation of new simulation models for new objectives that are linked to earlier models of a similar kind.

The concept of a generic model, which has a form that allows a single piece of simulation software to be used for projects covering a range of detailed applications, is seen as increasingly important. One particular approach to the development and validation of a generic model is described in (Smith, Murray-Smith & Hickman, 2007a – **submitted paper, [46]**) and (Smith, Murray-Smith & Hickman, 2007b – **submitted paper, [47]**). Such a generic structure allows reuse of simulation software for a wide range of different projects with relatively minor reorganisation in terms of the associated modules that are used to define the case under investigation. Although these two papers relate specifically to the development of a generic model of electro-optic systems, the central ideas and methodology are applicable to generic models in

other fields of application. The issues of validation of generic models present particular problems that are somewhat different from validation problems for more specific models and we address those issues in detail in (Smith, Murray-Smith & Hickman, 2007b – **submitted paper, [47]**).

Quite apart from the concept of a generic model, the ideas of modularity and component reuse are of key importance. These ideas mean that if we wish to build a new model for new given objectives we can select existing sub-models from a model base to serve as elements of the new model. The new model can thus be synthesised largely from existing modules.

A number of issues arise in the practical application of the concepts of model reuse and one of the most important is concerned with the issue of how component models can be designed so that they meet current requirements and also possible future needs (Cloud & Rainey, 1998, pp98-100). This can best be achieved by designing sub-models as building blocks for a family of applications rather than for a single project. A second important point relates to practical issues of flexibility in the large-scale reuse of sub-models and the extent to which the object-oriented approach that is commonly used in present-day general purpose programming languages can be applied within more specialised dynamic system simulation languages.

A paper by (Ostroversnik & Murray-Smith, 1998, **submitted paper, [48]**) presents a rationale for a modular and truly object-oriented dynamic system simulation language. Although many dynamic simulation languages claim to be object oriented they do not, in many cases, fulfil all of the required conditions (i.e, classes, instances, inheritance, etc.) to allow them to be regarded as truly object-oriented. One feature of particular importance for object-oriented simulation software is the requirement for sorting of code at run time rather than at the compile stage, as is more normal in simulation software. The paper presents a possible implementation of the sorting algorithm within a new object-oriented simulation language known as OOSlim (Ostroversnik & Murray-Smith, 1998, - **submitted paper, [48]**), (Ostroversnik, Murray-Smith et al., 2000 - **submitted paper, [49]**), (Ostroversnik & Murray-Smith, 1995, - *supporting paper, [50]*) and (Ostroversnik & Murray-Smith, 1996, - *supporting paper, [51]*). Sub-models implemented using the approach adopted in OOSlim are believed to represent one possible approach to the development of commercially available libraries of sub-models.

The application of the OOSlim approach is illustrated in (Ostroversnik, Murray-Smith et al. 2000 - **submitted paper, [49]**), where the well-known PHYSBE physiological simulation model is adopted as a benchmark. PHYSBE (McLeod, 1966) is an established model of the circulatory system in which each body part is considered as a blood storage compartment. There are nine body elements in total with the first group involving four compartments (head, trunk, arms and legs) in parallel with a so-called "Inner Cycle" which is made up of five blocks connected sequentially through valves. These compartments represent the vena cava, right ventricle, lungs, left ventricle and aorta. The head, trunk, arms and legs compartments are connected in parallel with the inner cycle compartments. This model is sufficiently large and complex to make it suitable for application of the OO approach.

In OOPhysbe the compartments representing the head, arms, trunk, legs and ventricles are similar and the only differences are the initialisation constants and their location in the model graph. An abstract sub-model is therefore appropriate for this and two classes (named "lump" for the external lumped elements and "ventricle" for both ventricles) can be formed. Then, instead of having six, largely duplicated, declarations in the simulation program there are only two class definitions and six short declarations and no code is duplicated unnecessarily.

Since a model is, by definition, only an abstraction of the system it represents, perfect accuracy is impossible to achieve. A key question is how best to establish the level of model quality appropriate for an intended application and ensure that the model satisfies that requirement before it is used. Although vitally important, this is a much neglected aspect of system modelling. As has been pointed out by many concerned with modelling and simulation (e.g., (Cloud & Rainey, 1998)), the validation of models cannot be separated from the model building process and validation techniques should be applied repeatedly during model development. If model building is approached as an iterative process confidence in a model should increase steadily from iteration to iteration.

This remaining sub-sections within this part of the thesis, together with the associated submitted papers, address a number of issues relating to model credibility, model verification methods and model validation methods. They describe, through selected published papers, a number of relevant and illustrative applications where issues of model quality are of great importance.

4.2 External Validation Methods

Errors and uncertainties in models arise in many different ways, including inappropriate assumptions, incorrect *a priori* information, inaccuracies in numerical solutions of model equations and errors in experimental data used in the model development process. A number of reviews of model quality issues and model validation procedures have been published (e.g., Murray-Smith, 1990b – *supporting paper, [52]*), (Murray-Smith, 1992 – *supporting paper, [53]*), (Murray-Smith, Bradley & Leith, 1993 – *supporting paper, [54]*), (Murray-Smith, 1995b – *supporting paper, [55]*), (Murray-Smith, 1998 – *supporting paper, [56]*), (Murray-Smith, 2000a – *supporting paper, [57]*), (Murray-Smith, 2006a – **submitted paper, [58]**) and (Gray, Voon & Murray-Smith, 1997 - *supporting paper, [59]*). The most recent of these (Murray-Smith, 2006a – **submitted paper, [58]**) is included as a submitted paper within this thesis.

Within engineering there are good examples, mostly in safety-critical application areas, where rigorous procedures are applied in the testing of models and where formal approval schemes for models are in place and routinely applied. However, the model development procedures used within many engineering organisations often involve surprisingly little systematic testing of models in terms of their useful range and limits of accuracy. External pressures, through developments such as "simulation based acquisition" and "smart procurement", are beginning to change this situation in some areas such as the defence sector. In general, however, progress in the field of simulation model quality enhancement is slow. This is in marked contrast with related areas such as software engineering. As was pointed out in a paper by (Murray-Smith,

2002 – *supporting paper, [60]*) there are important lessons that the simulation and modelling community could learn from computing science and, especially, software engineering in the context of model documentation, systematic testing and version control.

External validation, in which the behaviour of a simulation model is compared directly with the behaviour of the corresponding real system, is difficult in most practical applications due to the fact that models may contain dozens or even many hundreds or thousands of parameters that have values that are chosen by the user. Similarly, models may involve large numbers of output variables, all of which will exhibit differences from the corresponding quantities in the real system and these differences are likely to vary with time. For the purposes of assessing the overall quality of a given model it is important to know which of the output variables are of greatest importance for the given application and how much error can be tolerated.

Confidence in a prediction depends critically on confidence in sub-system models as well as in the complete system model. This is particularly important when sub-system models can be tested experimentally. Comprehensive and detailed testing at the sub-model level helps to establish confidence in the description at that core level and helps to allow it to be extended gradually to less well-defined situations involving the testing of the complete system model over a range of conditions. In the development of a new engineering system, test data are never available at the design stage. Historical data from earlier system designs of a similar kind may be helpful in evaluating the model but successful application of this approach depends on good documentation of models of those earlier systems and the tests to which they were subjected.

Comparisons (of a graphical kind or involving use of a quantitative measure) of data from a system and the corresponding model provide one obvious approach to external validation. Complications arise with methods based on response comparisons when several output variables have to be considered simultaneously or where un-modelled disturbances or measurement noise are significant. In such cases techniques based on system identification and parameter estimation may provide a useful alternative to direct comparisons and can offer additional physical insight concerning model limitations. Methods based on parameter sensitivity analysis are also important and the techniques of inverse simulation discussed in Section 3 have proved useful in a number of application areas. Methods involving expert opinion are also important in evaluating the suitability of a simulation model for a specific application. Details of each of these approaches to external validation may be found in (Murray-Smith, 1998 – *supporting paper, [56]*) and (Murray-Smith, 2006a – **submitted paper, [58]**). Discussion of other approaches to model validation, including model distortion methods and comparisons with current practice within the software engineering field may be found in (Gray, Voon & Murray-Smith, 1997 – *supporting paper, [59]*) and in (Murray-Smith, 2002 – *supporting paper, [60]*).

The external validation of nonlinear simulation models involves a number of important issues. Techniques for the identification of linear systems from measured experimental data can provide insight through establishing models for different operating points across the operating envelope of the system. These identified models can then be compared with linearised models derived from the full nonlinear

simulation model for the same set of operating conditions. Discrepancies between the identified models and the models derived from the nonlinear description have to be considered carefully and may lead to the credibility of the nonlinear model being questioned. If, however, the level of agreement between the two sets of models is considered adequate a second stage of the external validation process can be attempted. This involves comparison of responses of the nonlinear model with the responses of the real system for a range of large perturbations and is based on the direct comparison type of approach mentioned above. If, once again, the level of agreement is judged to be acceptable over an appropriate range of conditions the model can be released for use in the intended application. It can continue to be used until additional information or data raises new issues of model adequacy and the acceptability of the model has to be reconsidered in the light of such new evidence. This identification-based approach to the validation of complex nonlinear models is discussed in more detail in (Bradley, Padfield et al., 1990 - **submitted paper, [44]**).

Whatever approaches to external validation are adopted in a particular application there are several issues concerned with identifiability and robustness that need to be considered carefully. Identifiability has been discussed in Section 2 in the context of system identification and parameter estimation, and especially in connection with experimental design. Robustness in this context relates to factors such as the magnitude of error bounds on model parameters estimated from experimental test data, the accuracy and repeatability of model predictions, the effect of test input magnitudes and the length of available experimental records.

In a report by (Murray-Smith, 1991b – *supporting paper, [36]*) and a related lecture-series paper (Murray-Smith 1991c) robustness issues have been classified in the following way:

i) robustness and reliability of *a priori* information used in model development
ii) robustness of system identification and parameter estimation techniques used for model development or external validation purposes.
iii) robustness in terms of consistency and accuracy of the model structure and parameter values identified from system test data.

One very important point, which is often disregarded, is that when a model includes information obtained from the use of system identification and parameter estimation methods it is vitally important that the data sets used for external validation do not include any of the data sets already used in the development of the model. At a very minimum there should be two sets of data, one used for model development purposes (such as parameter estimation) and the second used to test the model in terms of its predictive capabilities.

The choice of data sets to be used in the testing of models that involve parameters or structures identified using other experimental data raises some interesting issues. Data sets used for the testing of models need to be broadly similar to the sets used in the identification process in terms of their spectral properties and amplitude distributions. On the other hand, it is clear that data sets used for testing should not be too similar to those used for identification and parameter estimation. Responses obtained from inputs other than those used at the identification and parameter estimation stage are bound to be different in terms of amplitude, frequency and

energy distribution. However, the differences in model and system behaviour for those new inputs may well be understandable on a physical basis and the results of the tests may still be very helpful in assessing the quality and limitations of the model.

One important point is that it is essential to properly match test data used for external validation to the intended application of the model. If that is not done it will not be possible to make decisions about the suitability and quality of the model in the context of that application. Proper use of the model may then be significantly restricted because of the set of conditions used for testing. Issues of this kind arise both in the validation of identified models derived from the application of conventional parameter estimation procedures for linear models and also from techniques leading more directly to the identification of nonlinear models.

In the case of linear models, the issue becomes one of obtaining experimental test records that are significantly different in form from the records used in the parameter estimation process but are similar in terms of the amplitude range and frequency range. This can present difficulties in practical system identification and parameter estimation applications and the issue of the choice of experimental records for the validation of identified models has been discussed in a number of papers and reports relating to helicopter system identification (e.g., (Murray-Smith, 1991a – *supporting paper, [34]*), (Murray-Smith and Padfield, 1991 – *supporting paper, [35]*), (Murray-Smith, 1991b – *supporting paper, [36]*), and (Hamel 1994)).

For the validation of nonlinear models the task of choosing appropriate test records is more complex since the test signals must excite the system in such a way that all the significant nonlinearities are fully explored while also covering the entire frequency range of interest.

4.3 Issues of Model Validation and Model Quality in Typical Application Areas

Model accuracy has, for a very long time, been recognised as an issue of central importance for the design of engineering control systems. For high performance closed-loop systems it is vitally important to have highly accurate models of the plant in a frequency range that includes the frequencies where the phase lag of the forward path system transfer function approaches 180 degrees (the so-called “cross-over” region). Model uncertainties within the cross-over region lead to major difficulties in guaranteeing that stability and performance requirements are met in the closed-loop system design (Murray-Smith, 1995a – *supporting paper, [22]*), (Murray-Smith, 1991b – *supporting paper, [36]*), (Murray-Smith, 2000a – *supporting paper, [57]*).

Other application areas, such as models that may provide a basis for the development of novel methods for non-invasive measurement in medicine and physiology (e.g., (Bache, Gray & Murray-Smith, 1981 – **submitted paper, [11]**), (Murray-Smith, 1990a – *supporting paper, [12]*), (Thamrin & Murray-Smith, 2007 – *supporting paper, [15]*), models that are used within system simulators for staff training or education (e.g., (Murray-Smith, Murray-Smith et al., 1995 – *supporting paper, [7]*), (Murray-Smith, 1990a – *supporting paper, [12]*)), models used in systems for

automatic fault detection or models that are used for prediction or hypothesis testing, all impose important requirements in terms of model quality if the application is to be successful. The sections that follow provide a few examples of fields in which some experience has been gained in the successful application of validation methods.

4.3.1 Helicopter flight mechanics model development

The validation of helicopter flight mechanics models is a topic of considerable practical interest. As in most other engineering applications, validation in this field has to be regarded as a relative concept and the validation procedures have to be related to the intended use of the model. Factors that are particularly important include the frequency range over which the model quality has to be established and the range of values over which particular response variables have to be considered (i.e. amplitudes). The paper by (Bradley, Padfield et al., 1990 **submitted paper, [44]**) is concerned with the validation of helicopter flight mechanics models intended for the prediction of flying qualities and vehicle dynamic performance. In terms of frequency the requirements extend beyond the range of human pilot control (approximately 5 rad/s) to cover the whole range of frequencies that could be involved in active control of the vehicle (about 20 rad/s). Amplitudes, specified through translational and rotational velocities and accelerations, depend largely upon the intended application of the model under investigation.

Techniques of system identification and parameter estimation, discussed in Section 2, have been applied successfully to the external validation of helicopter flight mechanics models (e.g., (Murray-Smith, 1995a – *supporting paper, [22]*), (Black & Murray-Smith, 1989 – **submitted paper, [29]**), (Leith, Bradley & Murray-Smith, 1993 – **submitted paper, [30]**), (Padfield & Murray-Smith, 1991 – *supporting paper, [37]*), and (Bradley, Padfield et al., 1990 **submitted paper, [44]**). Particular problems include the fact that helicopters generally involve a relatively high-vibration environment, allow only short test records due to marginally stable or unstable dynamics under open-loop test conditions, involve strong nonlinearities and have a strongly non-uniform flow field. During a ten year period from about 1985 to 1995 a number of software tools for state estimation, model structure identification and parameter estimation were developed in a collaborative activity involving the Royal Aerospace Establishment, Bedford, (latterly the UK Defence Evaluation and Research Agency, Bedford) and the University of Glasgow (Departments of Aerospace Engineering and Electronics and Electrical Engineering). Some of these software tools concerned with the implementation of specific identification and parameter estimation methods have been referred to already in Section 2.

One important aspect of external validation that has been emphasised in work relating to helicopter flight mechanics modelling is that the validation process may be best viewed as a form of *model calibration* aimed at establishing the range of conditions over which a given model may be used successfully. Outside that range of operating conditions the suitability of the model may be open to question. The external validation process can address issues of possible model refinement or correction in order to extend the range of applicability of a given model.

4.3.2 Modelling limitations for helicopter flight control system design

Good generic flight vehicle models are essential for the successful design of high-bandwidth full-authority active flight control systems for helicopters and other forms of rotorcraft, such as tilt-rotor aircraft. Published examples provide plenty of evidence that the achievable performance of helicopter flight control systems has been over-estimated in initial design studies because of limitations in the flight mechanics models of the vehicle (see, for example, (Murray-Smith, 1995a – *supporting paper, [22]*), (Murray-Smith, 1991b – *supporting paper, [36]*), (Murray-Smith, 2000a – *supporting paper, [57]*) for relevant discussion). These problems may not be appreciated until the flight testing stage and can results in costly redesign, extended flight test programmes and delays in certification. Improved modelling procedures and improved models offer significant benefits. Control system designs can always be made robust to compensate for poor model accuracy, but only at the expense of performance.

Accurate linearised models are especially important for the initial stages of flight control system design, as exemplified in the work of (Manness & Murray-Smith, 1992 – *supporting paper, [23]*) on the application of eigenstructure assignment techniques to helicopter flight control. That paper shows clearly that when one has confidence in the available model of the vehicle, very stringent performance requirements can be satisfied. However, good validated nonlinear models are also of great importance in the subsequent evaluation of designs. For example, published examples are avbailable which make it clear that the attainable bandwidth of high performance helicopters has often been overestimated in design. Differences between control system design approaches are probably of less importance than having a proven vehicle model which performs well in the critical ranges of frequency and amplitude, although robust control system design methods do have potential advantages over other methods.

The helicopter is nonlinear in its behaviour over most of its useful flight envelope and there is a need both for linearised models in the initial stages of control system design and for externally validated nonlinear simulation models in evaluating overall performance in the later stages of the design process. Issues of experimental design for model validation become particularly important in the context of this application area. For example, in a control system design context, the frequency content of test input signals must be chosen to give due emphasis to the part of the frequency range close to the nominal cross-over frequency, whereas in the context of other applications of flight mechanics models other requirements for test input design may be more important.

4.3.3 Issues of model quality in ship control system design

Accurate navigation and autopilot system design are important concerns for control engineers working in the marine field. As the size of vessels such as oil tankers has increased new problems have been identified due to incompatibility in terms of the rudder surface area in relation to the size of the vessel. In order to make a large manoeuvre a large turning moment must be generated by the flow of water over the deflected rudder. The magnitude to this turning moment depends on the rudder dimensions and the forward speed of the vessel. Since these attributes determine the

manoeuvring capabilities of the vessel they need to be accurately represented in any mathematical model used in the design of the ship steering controller.

A paper by (McGookin & Murray-Smith, 2006b – **submitted paper, [64]**) discusses problems associated with a model based on dynamic equations published by Fossen (1994) using data from a paper by van Berlekom and Goddard (1972). These problems became evident when the model was used in a paper by Çimen and Banks (2004) that attempted to develop a novel form of nonlinear optimal controller design for an oil tanker. Within the model, as applied by Çimen and Banks, the flow of water over the rudder involved incorrect terms which made the turning moment too large for a vessel of the size considered in the paper. This made the heading dynamics unrealistically sensitive to changes of rudder angle so that, in simulation studies, the vessel responded more rapidly than it should to controller commands. A modified form of relationship that had been used in a model discussed in an earlier paper by (McGookin, Murray-Smith et al., 2000a – **submitted paper, [65]**) represents the manoeuvring capability of a vessel of this size much more accurately.

The 2006 paper by (McGookin & Murray-Smith, 2006b – **submitted paper, [64]**) provides simulation results for standard open-loop manoeuvring tests. Responses of the modified and original models have been compared with data of Van Berlekom and Goddard (1972) and the simulated behaviour of the ship under open-loop conditions has been found to be significantly more realistic for the modified model.

The results of this investigation show that, although the controller design methodology applied by Çimen and Banks (2004) is a useful development in non linear optimal control theory, the ship responses presented in the illustrative example included in their paper are not realisable in a practical tanker application for this size of vessel. The controller design could not, therefore, be used in practice and a complete redesign, using the modified model suggested by McGookin and Murray-Smith (or some other form of improved model), is required.

4.3.4 Model quality and external validation in the development of generic models of electro-optic sensor systems

Electro-optic (EO) sensors convert photons into electrical signals and are used within electro-optic systems for imaging. A number of different technologies allow operation of electro-optic systems for the infrared, visible and ultraviolet waveband. Common applications include infrared search and track systems (IRST), missile warning systems (MWS) and thermal imager systems (TI).

EO sensor systems involve elements such as scanning and steering devices, optical components, detector elements with associated electron hardware and signal processing hardware and software. Models of complete electro-optic systems may involve dynamic systems (e.g motion of the target), atmospheric effects such as atmospheric attenuation, characteristics of optical and detector elements, electronic circuits and associated noise sources and a display system (the modelling of which may involve representation of the eye-brain system in an elementary way).

The assessment of the performance of an EO sensor system is a difficult, time-consuming and costly exercise. Although the performance of individual components

can be established readily under laboratory conditions, quantitative assessment of the complete system requires field trials on production or pre-production systems. As is the case with the helicopter flight control system design, problems identified in trials may well lead to costly redesign and, subsequently, to further testing. Field trials may also only cover parts of the operational envelope of the system and the successful completion of initial trials may not identify all the problems that could adversely affect the performance in an operational environment.

It is believed that modelling and simulation techniques can help to address some of the problems of EO sensor system development. Early assessment of overall performance within or beyond the normal operating envelope and insight regarding parameter sensitivities and inter-dependencies form important ways in which modelling and simulation can assist in design optimisation and minimise rework.

The paper by (Smith, Murray-Smith & Hickman, 2007a – **submitted paper, [46]**) outlines a generic approach to EO system modelling. Here the similarity of the structure of different types of EO system (all involving an optical chain, a detector, together with electronics, processing and display elements) provides the basis for the generic form of model. From a single generic model structure of this kind all specific types of EO system can readily be derived and the adoption of a generic approach facilitates model reuse in successive projects. The paper discusses the role of modelling and simulation in the EO systems field, from requirements engineering to system performance evaluation and design optimisation. This is relevant to many areas of engineering and especially for the development and design of integrated systems. In such applications a highly simplified conceptual model of the proposed complete system may provide a starting point, with the model then being further developed and transformed as the project progresses and firm design decisions are made.

One very important issue relating to generic models is the question of internal verification and external validation. The generic nature of the model gave rise to a number of special questions in the context of model quality and credibility. These issues are discussed in detail in a second paper by (Smith, Murray-Smith & Hickman, 2007b – **submitted paper, [47]**). Undoubtedly, issues of model credibility lead to more problems when a generic model is considered than they do in special-purpose models developed for a single application. This paper addresses the issues of model testing, internal verification and external validation for the generic EO sensor system model. A structural approach is proposed that develops increasing confidence during the modelling process through repeated bottom-up testing, structured verification procedures and carefully selected metrics for external validation. These validation metrics are based on a geometrical view of model outputs that may be compared with measurements using qualitative methods or quantitative approaches involving image processing, artificial neural networks or fuzzy pattern recognition. The advantages over traditional methods of external validation are most marked in the case of complex models with many key quantities, where this new approach not only provides useful insight about the credibility of the model but also about sensitivities. These tools for external validation have been applied, in conjunction with other more traditional metrics to the testing, verification and validation of the generic EO sensor system model configured as a thermal imager system.

One important development in this work, that may have value in other applications involving external model validation, involves taking a number of key system quantities and plotting these as radial lines on a polar diagram. Values are normalised and shown as points on the radial axes. These points are then joined by straight lines to form a polygon of the type shown in Figure 4.1. By creating a polygon of model results and a polygon of corresponding measurements on the same polar diagram an immediate indication of the validity of the complete model may be obtained. Generally, the more similar the polygon shapes the more valid the model is declared. Aspects of the system that are represented accurately are immediately obvious and areas requiring further analysis are also highlighted. Although they have been developed independently for model validation purposes, these diagrams have many features that are similar to those of the *Kiviat diagrams* (Grant & Murray-Smith, 2004 – *supporting paper, [66]*) that are used in the software engineering field for computer software and hardware performance evaluation.

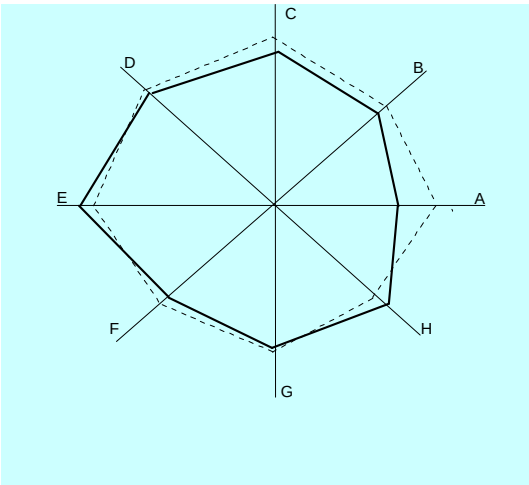

Figure 4.1. Example of polygon representation for model validation results. Here solid lines represent modelled results for eight different quantities while the dashed lines indicate the corresponding measured values. (Adapted from diagram in (Smith, Murray-Smith & Hickman, 2007b - **submitted paper, [67]**).

Diagrams of this kind, as shown through illustrative examples in (Smith, Murray-Smith & Hickman, 2007a - **submitted paper, [46]**), also have a role in analysing the effect of system parameters on overall performance metrics of a system. Shape-processed visualisation methods such as these lend themselves to image processing methods for quantification and a number of approaches have been considered (Grant & Murray-Smith, 2004 – *supporting paper, [66]*).

4.4 Issues of Model Quality in Model Reduction

Model reduction has for long been recognised as an important aspect of the process of developing a model for a specific application. For example, in the evaluation of aircraft handling qualities it is important to ensure that the model is of an appropriate

accuracy over a defined frequency range. Frequencies outside that range are not usually of very great importance in terms of the interactions between the pilot and the

vehicle. Similarly, as already discussed in Section 4.3.1, it is often important to ensure that the plant model in control system applications is highly accurate for a range of frequencies in the vicinity of the gain cross-over frequency but lower levels of accuracy can often be tolerated at frequencies well removed from that critical range.

Although the use of a relatively complex model that is applicable over a wide range of frequencies may not present difficulties in some types of application, there are other situations in which a simplified description with more limited applicability may be preferred. Situations of this kind can arise in applications involving real-time simulation where the use of a complex model that is applicable over a wide range of frequencies may introduce significant computational overheads.

One issue that is important in modelling of helicopters and other multi-input multi-output (MIMO) systems is to be able to derive a simple low-order model which has characteristics capable of approximating those of a higher order description for a specific frequency range. Simplified models of this kind can be important at several different stages of design.

A number of different time-domain and frequency-domain techniques exist and have been widely used, especially in the single-input single-output case. These include methods, such as those those of Davison (1966) and Bacon and Schmidt (1988), which involve the derivation of a model that includes only the dominant eigenvalues from a given higher-order description. Another group of methods involves the fitting of a low-order model directly to frequency response or time response data. In the time-domain case, an example of this approach can be found in the work of Anderson (1967), while in the frequency-domain the derivation of low-order models directly from frequency response data has been described by Levy (1959), Payne (1970) and Elliott and Wolovich (1980).

The paper by (Gong & Murray-Smith, 1993 – **submitted paper, [67]**) describes work carried out, in the context of helicopter modelling for flight control system design, on the development of a MIMO model reduction method which involves an extension of a complex curve-fitting approach described in the paper by Levy (1959) and further developed by Sanathanan and Koerner (1963) and by t'Mannetje (1973). The approach is transfer function based and uses a modified least-squares approach to fit transfer functions to the target frequency response data. The method presented by Levy (1959) involves minimisation of a sum of the squares of the differences between the absolute magnitudes of the frequency response values for the given data and the reduced model over a specific range of frequencies. The cost function in this case has the form

$$J = \sum_{k=1}^{n} \left| \varepsilon(\omega_k) \right|^2 \tag{4.1}$$

where n is the number of points in the frequency range considered and $\varepsilon(\omega_k)$ is the difference between the magnitude of the target frequency response and the frequency response of the fitted transfer function at frequency ω_k.

For the MIMO application the cost function is a modified form of the cost function applied by Levy (1959) and subsequently developed further by Sanathan and Koerner (1963) and by t'Mannatje (1973). Levy's method, which is an optimisation-based approach, was developed for application to measured frequency response data but, as described in the paper by (Gong & Murray-Smith, 1993 – **submitted paper, [67]**), it has been applied to model simplification. The significant development in this paper is the extension of Levy's technique from the single-input single-output case to multi-input multi-output situations. A number of illustrative examples involving models of an advanced fighter aircraft and also a large transport aircraft have been considered. It has been found that, in order to obtain satisfactory results, it is essential that two factors must be chosen with particular care. The first of these is a weighting factor within the frequency-weighted cost function used for optimisation that allows fitting errors in chosen parts of the frequency range to be given particular emphasis. The second is the number of points used within the frequency range of interest and the applications considered show that this has a definite optimum for a given model reduction problem. The examples considered show that the optimisation process converges very rapidly and that systematic investigation of the two factors that have to be chosen by the user is not difficult or time-consuming.

A different example of model reduction is discussed in a paper by (Bryce, Foord et al., 1976 – **submitted paper, [68]**) which describes the development and application of a model of a hydro-electric generator system intended for real-time simulation. This work related specifically to the power station at Sloy which, at the time when the work was carried out, formed part of the system owned and operated by the North of Scotland Hydro-Electric Board (NSHEB). The objective was to develop the real-time simulation as a test-bed for work that was being carried out on a fast-acting form of analogue electronic governor to replace the hydraulic governor that had been installed when the station was built in the late 1940s. This model also provided a basis for models used in the subsequent development of microprocessor-based governors. Although some tests on the real system were permitted during the model development process, tests to investigate the dynamics of the pipeline system, which is a vitally important part of the overall system model, were not possible for practical and safety reasons. Extensive modelling of the pipeline network had been undertaken previously by NSHEB engineers and a well-proven finite-element model existed, although this relatively complex and numerically intensive model could not be implemented within a real-time simulation. A decision was made to develop a lumped-parameter model of relatively low order that could capture the main features of the more complex finite-element pipeline model over the frequency range of most significance for turbine control. Versions of this lumped parameter description of different complexity were tested against the finite-element description using frequency-domain plots of the performance of the full and reduced models as a basis for comparison. A model of acceptable accuracy was then selected which could be implemented easily in real-time using the available computer hardware. This reduced model of the pipeline system was then integrated into the overall system model which was then subjected to external validation using data from tests carried out on the full system. The real-time

simulation was also subjected to detailed evaluation and testing for conditions that could not readily be included in the site tests. This evaluation involved experienced operators from the Sloy Power Station as well as NSHEB engineers. The eventual approval of the real-time simulation by the NSHEB engineers allowed it to be used as

a basis for evaluation of novel forms of governor under a wide range of operating conditions prior to their installation and testing on-site.

4.5 Discussion

The ideas of "verification, validation and accreditation" methodologies, "smart procurement" methods and the concept of "the model as a specification" are currently being emphasised in the defence procurement area on both sides of the Atlantic. Books and technical reports dealing with applied modelling and simulation topics in the context of very large and complex systems (e.g., (Cloud & Rainey, 1998)) are appearing in ever increasing numbers from government laboratories and agencies due, in part at least, to concerns about excessive cost and time over-runs in major projects. There appears to be a growing understanding that in many cases project failures can be traced back to failure to use modelling and simulation methods in an appropriate fashion at an appropriate phase of system development. This interest in issues of model testing and model quality for the design and development of very large systems is to be welcomed. However, it must also be realised that there are many aspects of model validation, model optimisation and model tuning that require very careful consideration even in the case of relatively simple dynamic models. Inadequate attention to model quality at an early stage, however simple the application, can lead to inappropriate design decisions that may be difficult and possibly expensive to correct at a later stage.

Issues of model quality and model validation cannot be separated from other processes of model development. The modelling of a real system is an iterative process in which testing, evaluation and tuning are of central importance and, whatever the context, it is essential to ensure that the model being used is appropriate for the purpose. An application based on a model that does not have the necessary quality is bound to lead to difficulties.

In the practical application of modelling and computer simulation methods, models are often developed on a one-off basis for a specific task. In industry, new designs of engineering systems similar in many respects to earlier systems often lead to completely new models. Also, these models are seldom subjected to a rigorous process of validation and are seldom documented in an adequate fashion. A poorly-documented model of questionable validity is unlikely to be helpful in the project for which it was intended. It is also unlikely to be considered for reuse in some future project which means that expensive manpower and resources may have been employed in creating a new model. This is undoubtedly short-sighted and wasteful.

As model libraries and generic descriptions are becoming more widely used in many application areas there is a new opportunity to try to ensure that model documentation and testing receives the necessary level of attention in future. Clearly the elements within model libraries have to be accompanied by information about the accuracy and limitations of each model or sub-model. Without documentation of an appropriate standard such libraries are going to be of little value and model documentation

should, therefore, always include information about the accuracy and limitations of the model with supporting evidence relating to the tests that have been performed. Such libraries should ideally involve precompiled sub-models and this necessitates the use of a simulation language having special features. As described in Section 4.1 above, an example of such a language is the OOSlim object-oriented simulation language developed through a cooperative project with the Jožef Stefan Institute, Ljubljana, Slovenia (Ostroversnik & Murray-Smith, 1998 – **submitted paper, [48]**), (Ostroversnik, Murray-Smith et al., 2000 – **submitted paper, [49]**).

In dealing with specific problems, whether to enhance our understanding of an existing system (as in physiology) or to improve the quality of a design (as in engineering), it is important to ensure that the necessary attention is given to the most relevant issues in each application. Modelling and simulation tools produce results that are of no practical value if they are applied in an inappropriate way and the old adage that "garbage in produces garbage out" applies as much in this field of computer applications as in any other. However, if simulation and modelling methods are applied in a highly focused fashion, with the right questions in mind, they can help to produce new insight that would be very difficult to obtain in other ways. The research reported in the paper by (Halliday, Murray-Smith & Rosenberg, 1992 – **submitted paper, [3]**) on the phenomenon of "driving" in the muscle spindle receptor provides an interesting example of the benefits of a focused approach of this kind. A relatively simple single-output model structure, with nonlinearities and parameter values determined from physiological evidence, was found (with some minor tuning of parameter values) to provide simulation results that matched very closely those obtained experimentally.

In other fields of application, such as helicopter flight mechanics, difficulties can be encountered due to the presence of close coupling of variables and parameters within the system. The fact that such systems are inherently multi-input multi-output in form means also that a number of output variables of the system have to be considered simultaneously and this tends to introduce additional problems. Although quantitative measures of performance, such as *Theil's Inequality Index* (Murray-Smith, 1998 – *supporting paper, [56]*) are appropriate for applications of this kind, the use of such criteria reduces the model quality assessment process to consideration of values of a single index which masks the true complexity of the situation and provides little or no physical insight. Methods for displaying results efficiently for multi-output situations and for models where there can be strong interactions between parameters are more desirable and the type of polygon diagram introduced in the papers by (Smith, Murray-Smith & Hickman, 2007a – **submitted paper, [46]**), (Smith, Murray-Smith & Hickman, 2007b – **submitted paper, [47]**) and discussed in Section 4.3 offer new opportunities. Further discussion of these diagrams may be found in the paper by (Grant & Murray-Smith, 2004 – *supporting paper, [66]*). Diagrams of this kind provide a basis for comparing different results from different models and results for different sets of parameters found from system identification and parameter estimation. They also allow results of sensitivity analysis to be displayed in a simple and efficient fashion. They are clearly applicable to problems in many areas where there is a need to depict relationships among multivariable data. The use of such diagrams in the context of detailed model analysis is believed to be novel, at least when first applied. One advantage of the polygon diagram approach to visualisation is that it is extremely flexible in terms of the comparisons that can be made. It is also appropriate for use with deterministic measures of performance such

as overshoot magnitude or frequency of oscillations. It might well provide a useful approach to the problems of comparing model and system behaviour in the type of situation that arose in the work on water turbine modelling outlined in Section 4.4 and described in (Gong & Murray-Smith, 1993 – **submitted paper, [67]**) and even in

situations involving simpler nonlinear system such as the coupled tanks systems used for laboratory teaching in control (Gong & Murray-Smith, 1998 – *supporting paper, [62]*).

5. Optimisation Methods in Nonlinear System Modelling and Nonlinear Control System Design Applications

5.1 Introduction

In the case of nonlinear systems some aspects of the model structure usually need to be determined from experiments as well as the values of some parameters. Identification of the model structure itself, including the nonlinear elements, can be difficult. Often a trial and error approach involving a mix of expert knowledge and experimental investigation is adopted to choose between several candidate models. Such an approach is time-consuming and, inevitably, somewhat subjective. Some form of automation of the procedure through the application of global optimisation techniques would allow a larger number of possible model structures to be investigated in a much shorter time.

The optimisation of linear and nonlinear systems is also of central importance for design in many areas of engineering and especially with highly integrated systems. Many aspects of present-day linear control theory have origins that relate in some way to optimisation methods but in the case of systems that involve significant plant nonlinearities, or applications in which controllers with intentional nonlinearities are introduced, the situation is more complex and there is considerable scope for the direct application of global optimisation methods.

5.2 Methods of Optimisation Considered

5.2.1 Simulated Annealing (SA)

Simulated annealing is a probabilistic hill-climbing technique that is based on the annealing of metals (see, for example, the work of Metropolis et al., (1953), Kirkpatrick (1983) and van Laarhoven and Aarts (1987)). This natural process occurs after the heat source is removed from molten metal and the temperature of the metal starts to fall as heat is transferred to the environment. At each temperature level the energy of the metal molecules decreases and the metal becomes more solid. This continues until the temperature of the metal equals the temperature of the surroundings and, at this stage, the energy has reached its minimum. The simulated annealing process mimics this natural annealing process as it searches for a solution.

In the SA algorithm the solution space is searched by imposing perturbations on the estimates of the parameters that are being optimised. These perturbations depend on a "temperature" index T and their magnitudes at any stage in the process are given by an equation of the form:

$$pert(T) = k \times T \times rand \tag{5.1}$$

where $pert(T)$ is the perturbation at temperature index T, k is a scaling constant and *rand* is a uniformly distributed random number lying between 0 and 1. In this algorithm the temperature index T becomes smaller with each iteration, thus reducing the size of the parameter perturbation, with large perturbations at the start of the

iterative process and small perturbations as conditions come close to the optimum. Each set of parameters arising from the application of this procedure is substituted into the equations defining the controller and the performance of the system with these parameters is evaluated through simulation. This performance evaluation involves comparison of the desired and simulated responses and is quantified using the relative cost (*C*). If the cost value is smaller than the previous best cost the new parameter set replaces the previous set. However, if the new cost is not smaller the new set of parameters is not immediately discarded and the cost value is subjected to a check in which the probability, *P*, of the cost associated with the new parameters (C_{new}) is compared with the previous best cost (C_{prev}) through the equation:

$$P = \exp\left(\frac{C_{prev} - C_{new}}{T}\right) \tag{5.2}$$

This has the same form as Boltzmann's Equation and the result obtained from its application is compared with a threshold number, *n*. If $P > n$ the new parameter values are accepted in the same way as if $C_{new} < C_{prev}$ but the new values are rejected if $P > n$. This so-called *Metropolis Criterion* (Metropolis et al., 1953) ensures that the SA avoids premature convergence to a local minimum.

Following this step the temperature index is reduced by the *annealing schedule* involving an equation

$$AS(T) = T_d = \gamma^d T_0 \tag{5.3}$$

where T_0 is the initial temperature, γ is the reduction constant and *d* is the number of iterations. The whole process is repeated until either the cost has reached some preset threshold level or the temperature value has become so small that the parameters are no longer being perturbed significantly. If the cost value has reached the minimum level, it follows that the SA should be giving the optimum set of parameters but if the temperature is too small the results may not be optimal.

5.2.2 Segmented Simulated Annealing (SSA)

Segmented simulated annealing (SSA) involves the application of a number of simple SA processes consecutively (e.g., (Atkinson, 1992), (McGookin, Murray-Smith and Li, 1996a – *supporting paper, [94]*)). SSA attempts, in this way, to overcome the limited convergence properties of the SA method if the parameters are not close to the optimum initially. Each of the consecutive runs starts at a different point in the search space so that, in effect, the search space is segmented into number of smaller regions. The final cost values, arising from the separate runs, are then sorted in ascending order and the smallest cost is taken as the optimum. The parameter values corresponding to the best cost value form the optimum result.

5.2.3 Genetic Algorithms (GA)

The *genetic algorithm* (GA) approach to optimisation is based upon the concept of survival of the fittest. The GA emulates the processes of evolution, with the strongest elements becoming stronger while the weakest elements are eliminated.

The solution of an optimisation problem using the GA methodology involves a stochastic search of the solution space using strings of integers, known as *chromosomes*, which represent the parameters that are being optimised. Each integer within these chromosomes is known as a *gene* and, in the context of the work being discussed here, each gene has a decimal value between 0 and 9. It should be noted that this is not the traditional GA approach where genes are binary quantities. The advantage of the decimal representation for this type of application is that it allows a wider range of possible values in smaller chromosomes.

An initial population of chromosomes is generated at random and these are decoded to obtain the corresponding parameters. These parameter values are then introduced into the system model or controller. A simulation is run and results are obtained for each set of parameters within the population, using a measure of performance based on a cost function similar to that used in simulated annealing. When the cost values are all found they are sorted into ascending order along with the corresponding chromosomes. As before, the smallest cost values are chosen as the best and are then subjected to operations involving *reproduction*, *cross-over* and *mutation.* This provides different points for analysis within the search space.

Reproduction is a procedure that involves retaining the best chromosomes (say 20%) for the next population. The remaining chromosomes are replaced by new chromosomes which are formed through the processes of crossover and mutation. This type of reproduction process is known as *rank-based selection* and it allows only the elite chromosomes to move on to the next iteration. This class of optimisation method is known as an *elite genetic algorithm* (Brooks et al., 1996).

Crossover is a process in which two chromosomes from the current generation (the *parent* chromosomes) are involved in a procedure in which some of the genes from one chromosome are interchanged with genes from the corresponding positions in the other. This process produces two new chromosomes (the *offspring*) and the procedure is repeated until there are sufficient offspring to replace the 80% of the present population having the worst cost values. A procedure known as *two-point crossover* has been used in the work reported in the papers included in this thesis.

Mutation involves selection, on a random basis, of a certain number of the genes in the current population and random alterations are then made to their values. This provides a random element within the GA search process and thus ensures that more of the search space is included.

Once the chromosomes have been changed to provide the new population they have to be evaluated, as was done for the previous generation. The whole procedure is then repeated for a predefined number of iterations (termed *generations*) to produce a final solution.

The 1996 paper by (Li, Ng et al., 1996 – **submitted paper, [69]**) provides an overview of the use of GAs in the design of a form of nonlinear control system and illustrates the application of this approach to design automation in the context of a practical, but relatively simple, application involving a laboratory-scale system. Further developments in terms of techniques have been reported in subsequent papers. These include a population minimisation process for genetic algorithms (McGookin, Murray-Smith & Li, 1997 – *supporting paper, [70]*) and the inclusion of non-uniform mutation (Alfaro-Cid, McGookin & Murray-Smith, 2005 – *supporting paper, [71]*).

5.2.4 Genetic Programming (GP)

Unlike the GA approach where, in a control engineering context, the objective is parameter optimisation, the methodology known as *genetic programming* (GP) involves an approach where there is no prior specification of the size, shape and structure of the solution and algebraic expression evolve from a database of nonlinear algebraic functional elements (Koza, 1992). Like the GA it is an evolutionary optimisation method but, unlike the GA, it does not require a structure that is rigid in form. While the problems to which the GA has been applied involve a set number of tuning parameters and a fixed-length string representation for the solutions, the application of genetic programming leads to a situation in which the size and shape of solution evolve dynamically. Thus, in a control context for example, genetic programming can provide a controller structure as well as an optimal set of parameters.

The GP approach to evolutionary computation allows optimisation of a tree structure representation of a symbolic expression. The tree structure has a variable length and is made up of a series of nodes. These nodes can be terminal nodes, representing an input variable or a constant. They may also be non-terminal nodes representing functions involving some form of operation on one or more variables of the system. Figure 5.1 shows an example of a tree structure and, in this particular case, the terminal nodes are system inputs and variables of the system under investigation or a constant. The non-terminal nodes, in this diagram, represent the operations of forming a square root, addition and subtraction.

The GP algorithm chooses possible elements from a library to build trees of this kind and each tree is evaluated as an algebraic expression to provide a fitness function value. There is a population of trees of this kind and this population evolves through the processes of crossover, selection and mutation towards a structure that is optimum in the sense of the chosen fitness function. The process is not deterministic and repeated runs are therefore likely to produce different solutions and analysis of a set of runs is necessary in order to produce an expression that is potentially useful.

5.3 Nonlinear Model Structure Identification using Genetic Programming

Genetic programming can be used to introduce an element of automation in the model structure identification process through the use of a fitness function which involves a measure of the agreement between the model and the system responses. A set of

possible model structures evolves, through many generations, towards a solution by means of a selection scheme based on "survival-of-the-fittest" and using evolutionary operators. At each stage the equation generated through genetic programming is combined with other equations involved in the model description to produce a simulated time response which must be compared with experimental data to give a fitness value for that model.

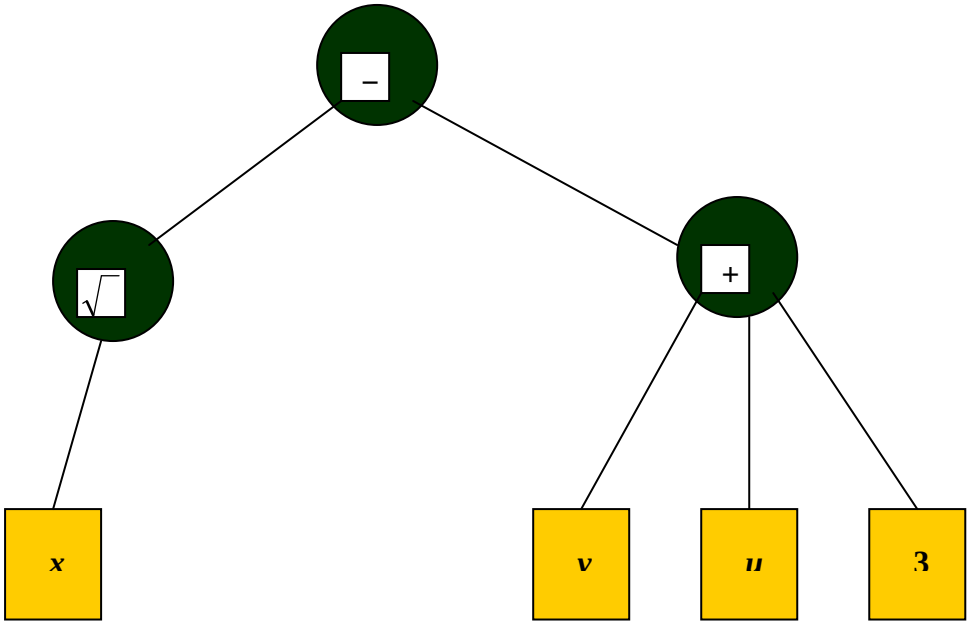

Figure 5.1: Structure of GP tree representing the function $y = \sqrt{x} - (v + u - 3)$. Here the circles represent non-terminal nodes whereas the rectangular blocks are terminal nodes.

The parameters of the candidate models can be estimated using numerical optimisation based on simulated annealing, or on simulated annealing combined with Nelder-simplex optimisation. It should be noted that gradient methods of optimisation cannot be used in the parameter estimation process because many models generated through the GP process contain linearly dependent parameters or parameters that have no effect on the model output. The fitness function value from the best parameter fit is then used by the genetic programming algorithm to define the fitness of that specific function tree.

Experimental design is of particular importance in the identification of nonlinear systems since the system must be excited over the whole frequency range of interest and also, in terms of amplitude, over the range of all the nonlinearities in the system. This means that a large training data set is needed. However, large data sets imply additional computational demands in terms of the chosen optimisation process so there is an inevitable trade-off between model accuracy and optimisation time.

The papers (Gray, Li, Murray-Smith & Sharman, 1996a – **submitted paper, [72]**), Gray, Murray-Smith et al., 1996b – *supporting paper, [73]*), (Gray, Murray-Smith et al., 1997 – *supporting paper, [74]*), (Gray, Weinbrenner et al., 1997 – *supporting paper, [75]*) and (Gray, Murray-Smith et al., 1998 – **submitted paper, [76]**) describe

the successful application of genetic programming methods to the identification of nonlinear model structures for continuous-time models. In this approach the candidate models may be described using both block-diagram and ordinary differential equation-based representations and prior knowledge of the physical system can be incorporated within those descriptions. The unknown dynamics evolve through the processes of genetic programming as an algebraic expression that forms part of the set of ordinary differential and algebraic equations describing the system. The genetic programming algorithm builds the models from a library of available functions. This library is very important and must be sufficiently flexible to allow for a wide range of functions, but not so general that a purely empirical representation can evolve. It should include basic algebraic operations (such as addition, subtraction, multiplication, squaring etc.) together with functions that represent common forms of dynamic characteristics (such as first or second-order linear sub-models) that might be expected to appear as elements within a complex description. Each member of the genetic program population represents a possible candidate model for the given system. It is important to note that any model structure identified using genetic programming needs to be validated using a data set that is different from the data set used for the optimisation.

Although not concerned with the use of genetic programming it is worth mentioning that genetic algorithms and simulated annealing have also been shown to be useful tools in system modelling from empirical data. The paper (Tan, Li et al., 1995 – *supporting paper, [77]*) gives an account of the application of these techniques to system identification and linearisation.

The papers (Gray, Li et al., 1996a – **submitted paper, [72]**) and (Gray, Murray-Smith et al., 1998 – **submitted paper, [76]**) include results obtained from the successful application of the GP approach to a number of different systems. These include a simple simulated system involving a linear transfer function and a pure delay element in cascade, a laboratory system involving a coupled tanks fluid flow system and a system for engine and rotor speed control in an MBB Bo105 helicopter. The results show that genetic programming can be used to fit a model intelligently, in terms of the topology and types of block structure employed, while the parameters can be estimated through the application of simulated annealing. With suitable constraints this approach could provide insight regarding physically-based model structures or could be used to validate a given nonlinear model using experimental data.

The paper by (Gray, Murray-Smith et al., 1998 – **submitted paper, [76]**) describes one particular approach to the use of genetic programming within the modelling process and describes its successful application to a number of simulated and real physical systems. The main applications considered involve test data from a coupled system involving a pair of water tanks and helicopter flight test data for modelling of helicopter engine dynamics.

Results from these applications show that genetic programming is a valuable tool for the modelling of nonlinear dynamic systems using experimental test data. This approach can allow nonlinear model structures to be developed through automation of the trial and error processes traditionally used for model structure estimation. It thus allows more candidate model structures and components to be evaluated. This method

allows poor features to be eliminated and good features of specific structures to be combined to give new forms of sub-model.

There is, however, an important issue in the selection of the fitness function that forms the basis for measuring the level of agreement between each candidate model and the measured response from the real system. It is essential that the fitness function should be chosen with due regard to all the available information about the real system and also the intended application of the model. The simulation routines used should return a value of the model fitness that is scaled in a suitable way for the GP selection operator.

Although the process of selection of the optimum description from among the candidate models is automated in this approach, the human skill in the choice of fitness function is vitally important for the ultimate success of the method. It is also important that the simulation methods used are numerically efficient and fast because each evaluation of the fitness function involves one simulation run and the number of evaluations needed may be large.

A model structure that has evolved from the application of the GP approach can often reveal new information about the system under investigation or can lead to additional experimental testing that can, in turn, throw new light on the physical processes involved.

5.4 Optimisation in PID, State Variable Feedback and H_∞ Control Schemes

Issues associated with the optimisation of classical controllers of the PID type have been explored in the paper by (Alfaro-Cid, McGookin & Murray-Smith, 2001c – *supporting paper, [78]*) and discussed further in (Alfaro-Cid, McGookin & Murray-Smith, 2006 –**submitted paper, [79]**). This work builds, to some extent, on earlier research reported by (Li, Tan et al., 1995 – *supporting paper, [80]*) at the 1995 IEEE Conference on Decision and Control involving linear control system design by genetic evolution with simulated annealing. Both the 2001 and 2006 papers involve genetic algorithm optimisation methods and include discussion of the encoding of each parameter value as a string of five genes to allow representation of controller parameters between 0.001×10^{-2} and 9.999×10^{3}. For a PID controller with three adjustable parameters 15 genes are needed to represent the controller. Results from the application of GA optimisation have been compared with results from conventional manual tuning of the PID controller for an example involving heading and propulsion control systems for physical scale models of two oil platform supply ships. These scale models (*Cybership I* and *Cybership II*) are used as test vehicles at the Marine Cybernetics Laboratory of the Norwegian University of Science and Technology (NTNU) in Trondheim. The Laboratory is equipped with a water basin with a wave generator. The objective in these studies was to make the vessel track desired dynamic responses with minimum actuator effort so that cost function, with two terms for each controller, has the form:

$$C = \sum_{i=0}^{tot} \left[(\Delta\psi_i)^2 + \lambda_i (\tau_{yi})^2 + (\Delta u_i)^2 + \lambda_2 (\tau_{si})^2 \right] \tag{5.4}$$

where $\Delta\psi_i$ is the *i* th value of the heading angle error, τ_{yi} is the *i* th value of the yaw thrust force, Δu_i is the *i* th value of the surge velocity error, τ_{si} is the *i* th value of the surge thrust force, *tot* is the total number of iterations and λ_1 and λ_2 are scaling factors. It should be noted that since the yaw thrust force and surge thrust force terms are of increasing importance as the error terms become smaller, these input terms tend to dominate the cost values near the optimum. This is why the two scaling constants are included in the cost function and a careful choice of these can ensure that the four terms within the cost are optimised equally. Although there is no difficulty in achieving acceptable responses using manual tuning methods, the time history for τ_{si} showed oscillations when the system was subjected to step changes in the reference inputs to both controllers simultaneously. This oscillatory behaviour was also observed in the case of the same controllers optimised using GAs and, since such behaviour could lead to excessive wear and possible fatigue in actuators, a modified form of cost function involving an additional pair of terms representing the rates of change of control inputs was considered. This led to the adoption of a modified cost function of the form:

$$C' = \sum_{i=0}^{tot}\left[(\Delta\psi_i)^2 + \lambda_i(\tau_{yi})^2 + \mu_1\left(\frac{\tau_{yi} - \tau_{y(i-1)}}{\Delta t}\right)^2 + (\Delta u_i)^2 + \lambda_2(\tau_{si})^2 + \mu_2\left(\frac{\tau_{si} - \tau_{S(i-1)}}{\Delta t}\right)^2\right] \tag{5.5}$$

which gave, with appropriate choices of the scaling constants μ_1 and μ_2, a satisfactory overall performance involving a good trade-off between tracking accuracy and actuator oscillations.

The paper by (Alfaro-Cid, McGookin & Murray-Smith, 2006 – **submitted paper, [79]**) compares GA-optimised PID controller performance with the performance of pole placement (PP) controllers also optimised using GA methods for the same application. Interestingly, it is shown in the paper that the optimised controllers provide very similar responses for both control configurations (PP and PID). In addition to extensive simulation studies, tests were carried out at NTNU in Norway on the *Cybership II* 1/70th scale model on which both types of controller were implemented. It is interesting to note that the implemented controllers required no adjustments beyond the tuning processes that had been carried out as part of the simulation studies.

The paper by (Alfaro-Cid, McGookin & Murray-Smith, 2008 – *supporting paper, [81]*) is concerned with the design and optimisation of H_∞ controllers. An H_∞ controller is a form of optimal controller which involves minimisation of an H_∞ norm instead of the more normal L_2 quadratic norm. The advantage is that the H_∞ norm allows specification both of the level of plant uncertainty and the signal gain from disturbance inputs to error outputs and this provides robust stability. The performance of a controller of this kind depends critically on the choice of certain weighting functions. A poor choice leads to poor control system performance. The paper describes the use of GAs for automatic optimisation of these weighting functions. Two approaches were considered and these involved (i) a conventional GA and also

(ii) a related method, developed by Dasgupta and McGregor (1992), known as a *structured genetic algorithm* (SGA). This latter approach is generally believed to be more suited to structural optimisation problems and, since the weighting functions in the H_∞ problem involve transfer functions, this was an appropriate choice of method. The application considered involved heading and propulsion control systems for an oil platform supply ship. Results obtained suggest that the SGA can be very useful for establishing appropriate weighting functions in that the tracking performance of the system developed using the SGA approach was better than the performance of the equivalent system designed using the GA approach. It is important to note that this improvement was achieved with weighting functions of lower order (with corresponding advantages in terms of implementation) and that actuator usage for the system designed using the SGA was significantly reduced compared with the usage level for the other system.

Work on a novel non-uniform mutation operator reported in a paper by (Alfaro-Cid, McGookin & Murray-Smith, 2005 – *supporting paper, [71]*) showed that optimisation results could be further improved in the case of H_∞ controllers. The inclusion of non-uniform mutation, together with a modified form of crossover operator involving exponential crossover probability, was shown to give significant benefits in an application involving ship control.

5.5 Optimisation Techniques in Sliding-Mode Controller Design

Sliding-mode controllers represent an important class of nonlinear control systems that have been widely applied. In its early development the approach received particular attention in the Soviet Union and in eastern European countries but has been very widely accepted in recent years as being a useful and highly practical approach to control system design and implementation. This acceptance is due to the inherent properties of control systems designed using this approach, which provide robustness in applications involving a wide range of operating conditions and stringent requirements in terms of disturbance rejection. Such performance could not be achieved so readily using linear controllers.

The favourable characteristics of sliding-mode controllers are provided by a switching term within the controller structure. This extends the action of the so-called nominal equivalent controller (which is usually a linear form of controller designed about a selected operating point) by providing control action over a wider operating envelope. The controller can then compensate for un-modelled dynamics and external disturbances.

The determination of the optimum set of values of the adjustable parameters within a sliding-mode controller is not a straightforward process due to complex interactions between these quantities. This makes the design process tedious and time-consuming and is one of the reasons why nonlinear controllers of this type have not been more widely used in industrial applications. There is a clear need for a more automated design process.

A number of different approaches to the automation of the design process for sliding-mode controllers have been considered, mainly in the context of marine applications. The findings from these investigations of different optimisation tools are, however,

quite general and are applicable to many problem areas. The methods selected for comparison are simulated annealing (SA), segmented simulated annealing (SSA), genetic algorithms (GA) and genetic programming (GP).

The paper by (Li, Ng et al., 1996 – **submitted paper, [69]**) describes the application of design automation based on the use of GAs to the development of a sliding-mode controller for a two-input, two-output system. The specific application involved control of liquid levels in a pair of coupled tanks used for teaching. Results showed that design automation based on GAs avoided tedious trial and error methods. It also produced a system which had a performance that was better than the performance of designs produced manually. This is extended in (Ng, Li et al., 1995 – *supporting paper, [82]*) to the design of sliding mode controllers that incorporate fuzzy elements. The idea, in this case, was to incorporate fuzzy control to the switching logic to overcome problems of chattering in conventional sliding-mode systems. The adoption of the fuzzy approach increases the complexity of the design and makes a trial-and-error approach very hard to apply successfully. Some form of automated design method really becomes essential in this case. The paper describes the development of methods involving tournament and rank-based genetic algorithms. The method was applied very successfully to the control of a two-tank coupled liquid-level system.

The optimisation of non-linear control systems by genetic algorithms is also discussed in the paper by (McGookin, Murray-Smith et al., 2000b – **submitted paper, [83]**). This paper involves applications to ship control systems and two specific systems are considered. Both systems relate to a nonlinear model of a 190,000 ton oil tanker. One system is concerned with course changing and the other with track keeping through a form of line-of-sight autopilot. Various operating conditions were used in the evaluation of system performance. In the case of the course changing controller these involved changes of desired course and changes in water depth. For the case of the track-keeping controller, the system performance was tested in terms of positional accuracy for both deep water and shallow water conditions and for different loading conditions. The controllers used for both applications were of the sliding-mode type using a derivation by Fossen (1994) and Slotine and Li (1991) in which switching action is provided by a hyperbolic tangent function. In order to smooth the switching action a boundary layer is incorporated.

The switching action of the sliding mode controller determines how robust the system is to model uncertainties and also to external disturbances, such as waves and wind forces. Four parameters have to be optimised in the controllers and these key parameters have to be adjusted so that an appropriate cost function is minimised in each case considered. The results presented in the paper show that optimisation based upon the use of genetic algorithms can be very effective in obtaining values of design parameters in complex nonlinear controllers and that these controllers perform well in simulations. It is suggested that the form of sliding-mode controller presented in the paper has a structure suitable both for the course changing and track keeping applications. It is also suggested that the chosen form of controller exhibits excellent robustness for the complete range of operating conditions considered. The type of sliding-mode controller developed in the course of this investigation was therefore a strong candidate for further testing and evaluation on a vessel or using a scale model vessel in a testing tank.

A further more detailed publication by (McGookin, Murray-Smith et al., 2000a – **submitted paper, [65]**) describes the application of sliding mode control, optimised using genetic algorithms, to the performance optimisation of a navigation system for the same tanker model as that discussed above. This fully autonomous navigation system involves two major sub-systems in control systems terms. The first of these is a line-of-sight autopilot which determines the desired heading of the tanker from positional information and the second is a heading control system. The nonlinear sliding-mode control features arise in the heading control loop and genetic algorithms are applied to the optimisation of that sub-system. The overall system performance has been evaluated for a variety of different operating conditions for the tanker model, including different waypoint courses, altered waypoint acceptance radii, different loading conditions and different forward velocities for the vessel.

Simulated responses for the optimised system show that the design criteria for the optimisation were satisfied and that the solution compares favourably with designs derived using traditional engineering judgement alone. The overall conclusion from this investigation was that genetic algorithms can allow a general-purpose navigation system to be designed with sliding-mode controller parameters which provide a very satisfactory level of performance robustness. In most of the cases considered the system completely satisfied the design criteria, but situations involving a reduction in forward velocity affect the flow over the rudder and this reduces the turning moment until a point is reached where there is insufficient torque to complete the commanded manoeuvre.

The work on optimisation of sliding-mode controllers has been taken forward in a significant way in work described in a more recent study by (Alfaro-Cid, McGookin et al., 2005a – **submitted paper, [84]**). This involved implementation and extensive testing of sliding mode controllers for propulsion and heading control on the oil platform supply ship (*Cybership II)* at NTNU in Norway. This vessel has a tunnel thruster at the bow, two main propellors at the stern and two rudders at the stern. Facilities on the model and in the basin allow measurements of the heading angle and (x,y) coordinates of the vessel. *Cybership II* is equipped with an on-board personal computer (PC) but control calculations are performed in real-time using an on-shore PC which communicates with the on-board computer through a wireless link The simulation work required for design optimisation was based upon a nonlinear hydrodynamic model of the vessel.

Controllers optimised through simulation studies (without waves) have been subjected to tests in the water basin both in the presence of wave disturbances and in still water. Without waves the results showed that the tracking performance of the control system was excellent and that in the presence of waves the tracking performance of the system was not degraded significantly. The results for controllers optimised in the presence of simulated waves were less satisfactory, with a significant reduction of control effort but a relatively poor response in terms of surge error.

The paper by (McGookin & Murray-Smith, 2006a – **submitted paper [85]**) on the optimisation of SM controllers for submarine manoeuvring using SA, SSA and elite GA methods builds, in part, on a paper by McGookin, Murray-Smith and Li presented at the UKACC Control ’96 Conference (McGookin, Murray-Smith & Li, 1996b –

supporting paper, [86]). Two controllers were involved in this investigation, one for depth control of the vehicle and the other for heading control. In this case there is significant dynamic cross-coupling between the two systems. Results showed that, while SA is a useful local optimisation technique, it is not particularly useful as a design automation tool. The reason is that it requires prior information about the region of the parameter space in which the optimal solution lies. It is, however, a potentially useful method for fine tuning of a controller that has been designed initially by some other method. Application of the elite GA provided results that were good in many respects but showed problems in that this global search method provided very few incremental changes in the final generations. This means that there was no fine tuning of results and there were 16 candidates in the final generation that exhibited similar characteristics. However, this does imply that a region has been found that is near the global optimum and one can therefore have confidence in the final solution provided by the GA. The SSA approach was found to overcome the restrictions of the SA method and could provide the basis of a useful global optimisation method. In comparison with the GA, however, the SSA approach had only 4 final candidates (compared with 16 from the GA method) and the confidence level is inevitably lower. Both the GA and SSA methods have advantages and disadvantages for this application but, on balance, it was concluded that the GA approach provided the best overall performance.

Work presented at the 2005 IFAC World Congress in (Loo, McGookin & Murray-Smith, 2005 – *supporting paper, [87]*) involves the application of sliding-mode control for feedback controller design combined with inverse model control for a tanker. In this case it was found that the sliding-mode controller could act as a corrective controller with the inverse model acting as a feed-forward controller. The use of inverse model feed-forward control in conjunction with a corrective feedback controller was found to provide benefits when compared with conventional feedback controllers. In particular the sliding-mode control scheme benefits from the combined control structure and the two controllers together outperformed conventional feedback control methodology. This topic is explored in more detail in Section 6 in the context of inverse simulation methods applied to control system design.

Ship control applications involving sliding-mode controllers and other forms of nonlinear controllers are reported in a number of additional publications including (McGookin, Murray-Smith et al., 1997a – *supporting paper, [88]*), (McGookin, Murray-Smith et al., 1997b – *supporting paper, [89]*), (McGookin, Murray-Smith & Fossen, 2000 – *supporting paper, [90]*) and (Alfaro-Cid, McGookin & Murray-Smith, 2001a, -*supporting paper, [91]*). Gain scheduling controller analysis and design using genetic algorithms is discussed in (Gray, Li et al., 1997 – *supporting paper, [92]*). The use of genetic algorithm optimisation in the development of a ship navigation system is described in (Alfaro-Cid, McGookin & Murray-Smith, 2001b – *supporting paper, [93]*). Other work carried out on the application of advanced optimisation methods to sliding mode controller design includes research on the application of segmented simulated annealing methods (McGookin, Murray-Smith & Li, 1996 – *supporting paper, [94]*). Results of research on the specification of a control system fitness function using constraints for genetic algorithm based design methods may be found in (Gray, Li et al, 1995 – *supporting paper, [95]*).

5.6 Controller Design using Genetic Programming

The 2005 and 2008 papers by Alfaro-Cid, McGookin, Murray-Smith and Fossen (Alfaro-Cid, McGookin et al., 2005b – *supporting paper, [96]*) and (Alfaro-Cid, McGookin et al., 2008 – *supporting paper, [97]*) are both concerned with the application of a GP approach to the selection of controller structures for heading and propulsion systems for a surface vessel. The aim was to provide good tracking of the desired response in each case while minimising control effort. The function set involved 11 functions that included variations on PID control, sliding-mode control and pole placement techniques. The vessel considered in this work was the *Cybership II* scale model of an oil platform supply ship which was described in more detail in Sections 5.4 and 5.5. Experimental evaluation of the controllers optimised by the use of GP methods was carried out at NTNU.

Optimisation, with and without wave disturbances, converged to trees that gave very similar control strategies and this was considered encouraging. The best results involved a controller structure that was based on a hyperbolic tangent function in the heading control loop (representing a form of sliding-mode control approach) and either a proportional term or a second hyperbolic function in the propulsion loop. However, the terminal values resulting form the search mean that the hyperbolic functions were operating in the proportional range rather than in the switching area. In the case of the propulsion loop this meant that the system was effectively providing proportional control while, in the case of the heading loop, it is shown in the paper (Alfaro-Cid, McGookin et al., 2008 – *supporting paper, [97]*) that the solution found effectively involves full state-feedback control.

Another recent paper describing advances in the application of genetic algorithms and genetic programming methods to ship control problems is (Alfaro-Cid, McGookin & Murray-Smith, 2009 – *supporting paper, [98]*) which presents results of a comparative study of genetic operators for controller parameter optimisation.

5.7 Other Approaches involving Nonlinear Controllers

5.7.1 Artificial Neural Network (ANN) methods

Artificial neural network (ANN) and fuzzy logic methods have received considerable attention for nonlinear control system applications in recent years. These areas of research have often been grouped together with evolutionary computing methods under the heading of “biomimitic” approaches since they have some links with biological systems. Although the biological analogies are not emphasised in the work presented in this thesis, these methods do provide an interesting alternative to more classical methods for nonlinear control system design. Applications have been concerned mainly with laboratory-scale applications and with problems of ship-steering control.

In contrast to other work concerned with direct neuro-controllers (e.g., (Häussler, Li et al., 1995 – *supporting paper, [99]*), the approach emphasised in this thesis for the implementation of neural network based controllers involves training the network to

behave like a specific form of conventional controller. Input and target data for the training process can be generated from the input and output of the controller when operating in normal closed-loop fashion in conjunction with the plant. It should be noted that the simple replacement of a conventional controller by an equivalent ANN controller would give no benefits since this would require the design of the conventional controller by traditional methods and then the training of the ANN controller. The potential advantages come only if it is possible to train a single artificial neural network, using a number of conventional controllers (optimised for different operating points), to cover a range of conditions that would otherwise necessitate the use of some form of scheduled controller system.

The main emphasis in the research on artificial neural networks included in this thesis is on applications involving ship steering control. The first work carried out at Glasgow in this field, by (Simensen & Murray-Smith, 1995 – **submitted paper, [100]**), involved simulation studies in which a feed-forward network was trained to behave like a feedback linearisation controller. The ship model used was a relatively simple description involving an extended version of Nomoto's first order model (e.g., (Fossen, 1994)), which has been used as the basis for many other ship steering studies. The network configuration used was a conventional feed-forward network with six inputs, one hidden layer and one output. Tan-sigmoid activation functions were used on the hidden layer neurons and a linear activation function on the output layer neuron. Bias inputs were applied to the hidden layer and output layer neurons. The back propagation algorithm, with momentum and adaptive learning, was used for training. The results obtained showed that the approach could yield a control system which provided a satisfactory level of performance for a range of operating conditions.

The success of the neural-network controller was found to depend very much on the choice of input variables and on the training data set being used. Physical insight was recognised as an important factor for both of these issues. One particular issue investigated, using simulation, concerned the effect of external disturbances and whether or not disturbances should be included in the training data. The conclusion reached was that, for this application at least, training data should include disturbances due to the fact that this makes the training data more varied in character and this appears to yield a more robust form of controller.

A second paper by (Unar & Murray-Smith, 1997 – *supporting paper, [101]*) investigated the application of radial basis function (RBF) networks to problems of ship steering control. For training and testing purposes models of three different ships were considered. A supervised learning strategy was applied for training the networks, with PD and PID controllers designed for different forward speeds being used as supervisors for the training process, as in the earlier work described in (Simensen & Murray-Smith, 1995 – **submitted paper, [100]**). The networks were found to be capable of yielding satisfactory performance at different forward speeds within the range considered in the training phase. That paper includes comparisons of the performance of the RBF networks with the performance of conventional MLP type feed-forward networks trained using back-propagation methods. It was shown that adoption of the RBF type of network can provide benefits in terms of reduced training time and improved performance robustness in some cases.

A subsequent paper (Unar & Murray-Smith, 1999 – **submitted paper**, **[102]**), builds upon the foundations established in (Simensen & Murray-Smith, 1995 – **submitted paper, [100]**) and (Unar & Murray-Smith, 1997 – *supporting paper, [101]*) and describes both a successful investigation of radial basis function networks for ship steering control and also discusses the use of local model networks, as discussed in Section 2, for the representation of ship dynamics. The conclusions reached in that 1999 paper are that radial basis function networks allow a controller to be derived that incorporates the characteristics of a number of conventional controllers and that this form of network has some advantages over multi-layer perceptron type networks for this application. These advantages are in terms of the simpler network structure and the improved approximation properties of the resulting neural network based controller. The paper also shows that local model networks, trained from simulation data, could be used successfully to represent ship dynamics for a range of operating conditions. This takes account of the limitations that are known to exist (see e.g., (Shorten et al., 1999)) for local model networks when operating far from the equilibrium points at which the local models were established.

5.7.2 Nonlinear control through velocity-based linearisation methods

A paper by (Kocijan & Murray-Smith, 1999 – **submitted paper, [103]**) describes the application of velocity-based linearisation methods to the design of a gain-scheduling controller for ship steering. The main advantage of this type of approach is that it links nonlinear control system design with the type of knowledge required for the analysis and design of conventional linear control systems. In this approach a nonlinear controller is designed via a velocity-linearised nonlinear system description. The extended form of Nomoto's first order model was again used in this work (as in (Simensen & Murray-Smith, 1995 – **submitted paper, [100]**), (Unar & Murray-Smith, 1997 – *supporting paper, [101]*) and (Unar & Murray-Smith, 1999 – **submitted paper**, **[102]**)). Robustness may be achieved during the linear phase of the design process and is preserved when the nonlinear form of controller is implemented. Performance requirements in terms of tracking of the reference model signal were found to be met for the full operating range. Stochastic robustness analysis showed that this nonlinear controller successfully performed its task regardless of plant variations over a wide range. The advantage of this approach is that it provides a single controller of moderate complexity which is valid for a wide range of operating conditions and is robust to parameter variations. It is thus similar in its objectives to the work described above involving the use of ANN methods for ship steering control. One perceived advantage of the velocity-based linearisation method over the approach based on ANNs is that it provides increased physical insight.

5.8 Discussion

This section of the thesis has highlighted the potential for automation of some aspects of the processes of system modelling and controller design. Although computational tools such as genetic algorithms and genetic programming can help to eliminate trial and error methods and make the processes of modelling and design more systematic, it must be emphasised that the use of automation in this way does not diminish in the importance of the investigator or designer. The use of these advanced optimisation methods undoubtedly changes the nature of some of the tasks involved. Their use

eliminates some subjective elements of the procedures but inevitably introduces others, such as the choice of fitness function. The main benefit is that, when properly used, these powerful methods for global optimisation allow a significantly larger number of solutions to be considered than would otherwise be possible.

Similar issues arise in the use of artificial neural networks in controller design. It is believed that the approach considered in this case, involving the training of an artificial neural network to capture the characteristics of a number of conventional controllers which have been optimised separately for a number of different operating points, has particular benefits in that it builds upon the expertise of the designer. The approach produces a single "scheduled" type of controller that can give satisfactory control system performance for a wide range of operating conditions within the limits for which it has been trained. This produces a simpler controller to implement in software than would be possible with a conventional scheduled control scheme. The approach may be viewed as being similar to the use of artificial neural networks to represent a complex multi-input multi-output look-up table for nonlinear function generation. Physical insight and understanding of the dynamics of the real system were found to be important factors in the selection of training data sets and the input variables for the neural-network based controller.

An alternative approach to gain scheduled controller design, considered in Section 5.7.2, involves velocity-based linearisation. It is believed to have potential advantages over methods based on artificial neural networks due to the fact that the approach retains the possibility of interpreting features of the overall system performance using basic physical insight.

6. Inverse Simulation Methods for Control System Design Applications

6.1 Inverse Simulation Techniques in Control System Design

Control schemes for output tracking based on a *two degrees-of-freedom* approach, of the type shown in Figure 6.1, frequently involve methods of design based on model inversion. These techniques have been used extensively to design feed-forward controllers. Key publications in this area include the papers by Francis and Wonham (1976), Hirshorn (1979), Isidori and Byrnes (1990) and Devasia, Chen and Padden (1996). In the block diagram $\boldsymbol{K_{ff}}$ is a model-inversion based feed-forward controller and $\boldsymbol{K_{fb}}$ is a feedback controller. If the inverse model in the feed-forward path were perfect and if the system was not subject to any external disturbances there would be no need for the corrective feedback pathway.

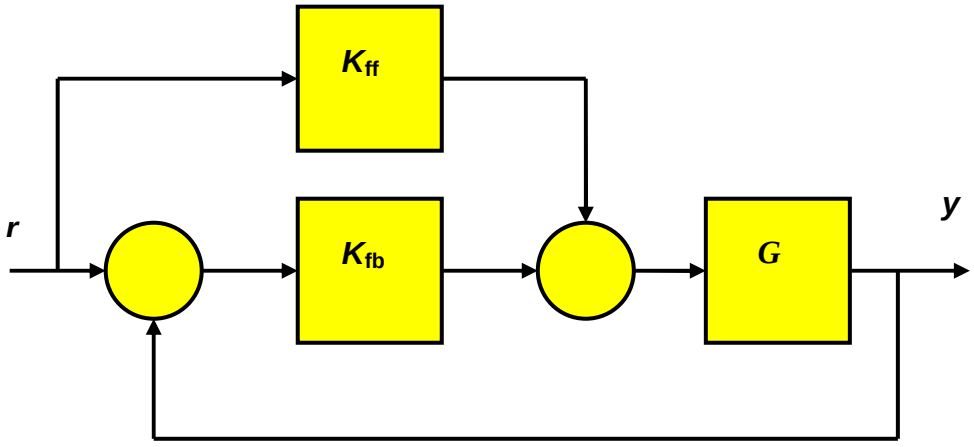

Figure 6.1: Block diagram of model-following control system based on the two degrees-of-freedom approach involving a feed-forward controller K_{ff} and a feedback controller K_{fb}.

The control system structure of Figure 6.1 arises because it is impossible to produce a perfect inverse model and external disturbances are present in almost all control system design problems. Thus, for practical purposes, the corrective feedback controller is essential to provide the control action that is not provided by the feed-forward controller to compensate for external disturbances and plant model uncertainties. The design and analysis of schemes of this kind has been an active topic of research since the 1990s and such systems have received particular attention in the context of aircraft applications. The feedback controller may be designed by any one of a number of well known methods such as PID control, the H_∞ algorithm, the linear quadratic approach, or through sliding mode control principles.

Inversion of the system dynamics for feed-forward system design, although well proven through a number of published studies, presents practical difficulties in the case of nonlinear plant models. The mathematical basis of the approach leads to problems in terms of translating the approach into a technique that can be applied routinely by design engineers in industry. The difficulties are particularly important in

the case of systems that have to be represented by high–order models, as is often the case in aircraft flight control or marine applications. Some success has been reported in the use of inverse models for feed-forward control schemes based on linearised plant descriptions. An example of an application in the marine area may be found in the paper by (Loo, McGookin & Murray-Smith, 2005 – *supporting paper*, *[87]*).

Inverse simulation algorithms, of the types described in Section 3 of this thesis can generate control inputs such that the mathematical model can follow an ideally defined trajectory. Thus, model inversion and inverse simulation both involve specification of a required manoeuvre and determination of the inputs required to follow that pre-defined manoeuvre. Replacement of an inverse model in a control system design process by an inverse simulation does not appear to be a difficult step, provided the inverse simulation can satisfy all of the conditions that must be met for the successful implementation of an inverse model within a control system.

Previously, inverse simulation does not appear to have been used within output-tracking schemes, except for the work of Avenzini (2001) who has investigated the possible use of inverse simulation to provide the reference input for a controlled helicopter model.

The papers by (Lu, Murray-Smith & McGookin, 2006 – *supporting paper*, *[104]*), (Lu, Murray-Smith & McGookin, 2007 – **submitted paper, [105]**) show that inverse simulation can provide an alternative to model inversion for some important cases. The type of system considered involves a combination of feed-forward and feedback control and corresponds to the general form of block diagram of a model-following control scheme of the type shown in Figure 6.1.

In this work inverse simulation was used to design the feed-forward controller and the mixed sensitivity H_∞ algorithm (see e.g., (Skogestad & Postlethwaite, 1996)) has been used for the design of the feedback controller. Applications described in the paper (Lu, Murray-Smith & McGookin, 2007 – **submitted paper, [105]**) involve a linear non-minimum-phase helicopter model and a nonlinear container ship system. A further example is described in (Lu, Murray-Smith & McGookin, 2006 – *supporting paper, [104]*) and this involves an application based on a nonlinear model of the HS125 fixed-wing aircraft, where results from inverse simulation are compared directly with results from the application of model inversion techniques. The inputs found from the application of the two approaches are identical.

The overall conclusions of the studies described in (Lu, Murray-Smith & McGookin, 2006 – *supporting paper*, *[104]*) and (Lu, Murray-Smith & McGookin, 2007 – **submitted paper, [105]**) are that it is feasible for inverse simulation to replace model inversion in output tracking applications. In the case of minimum-phase systems, for an appropriate choice of discretisation interval, inverse simulation provides a viable alternative approach. The inverse simulation method is easier to apply, generally, than model inversion. Depending upon what can be achieved in terms of zero redistribution within the process of inverse simulation it may also be possible to apply inverse simulation for linear non-minimum-phase systems. One major advantage of the inverse simulation approach is that the computational overheads are modest compared with those involved in dynamic inversion.

6.2 Inverse Simulation in Man-Machine Control Systems Investigations and the Predictive Inverse Simulation Approach

As mentioned in (Bradley, Padfield et al., 1990 – **submitted paper, [44]**) and other papers (e.g., (Rutherford & Thomson, 1996)), the investigation of inverse simulation techniques for the validation of helicopter flight mechanics models highlighted an issue when a defined standard manoeuvre, such as a side-step or quick-hop manoeuvre, was used as a basis for comparing flight test results with model predictions. While it is straight-forward to use inverse simulation methods to find the pilot control-inputs that are appropriate for flying the given manoeuvre, flight test results tend to show control-input time histories that are different in form from those predicted from the simulation model. While part of the difference is inevitably due to errors in the mathematical model, there is a second factor that is also very important. In the flight testing case, the pilot is continually adjusting inputs during the manoeuvre to ensure that the helicopter keeps as closely as possible to the desired flight path. Thus, there is a complex process of feedback present that does not exist in inverse simulation with an open-loop flight mechanics simulation model. While this is important in the context of the external validation of simulation models, it also suggests that benefits could result from a study of inverse simulation in pilot-in-the-loop modelling and thus also in the more general context of man-machine control systems.

The paper by (Cameron, Thomson & Murray-Smith, 2003 – **submitted paper, [106]**) describes the development of an approach to aircraft handling qualities investigation using inverse simulation together with a pilot model. This combination provides an integrated description of the complete system involving man and machine. In order to include pilot-generated effects within the data generated by inverse simulation, the output obtained from an inverse simulation run is applied as input to a closed-loop system model that includes the dynamics of the vehicle and a highly simplified model of the pilot. This approach has been used in an investigation simulating a predefined mission task involving a lateral manoeuvre. For this, a simple mission-programmable real-time flight simulator was constructed to allow experimentation using human subjects and thus estimation of parameters for the pilot model. The conclusions of that investigation suggested that, in principle, inverse simulation methods and a simple real-time simulator could be used to generate simulated flight data for handling qualities investigations at an early stage in the design of a new vehicle. The principles of this approach could be applied to other man-machine control problems involving a human within the feedback loop.

It is recognised that simple inverse simulation techniques can produce control strategies for aircraft applications that an experienced pilot would not normally adopt. This could be, as discussed in the first paragraph of this sub-section, because pilots use feedback on a continuous basis to monitor the vehicle's performance and this feedback is of vital importance when external disturbances are present. As indicated above, such feedback pathways are not normally included in the models that are used for handling qualities investigations based on inverse simulation methods. Another reason why solutions provided by simple inverse simulation algorithms may not match the strategies adopted by pilots is that, in inverse simulation, no account is taken of constraints that are well known to experienced pilots and are taken into account in determining appropriate control actions. These constraints include

mechanical limitations of actuators, limitations in terms of main rotor and tail rotor torque and structural limits of key components of the vehicle.

It has been shown in the 2007 IFAC Symposium paper by (Bagiev et al., 2007b – **submitted paper, [108]**) that conventional inverse simulation can be improved by incorporating predictive capabilities for applications involving manoeuvring flight. As noted in Section 3, conventional approaches to inverse simulation, such as the differentiation or integration based methods involving the Newton-Raphson algorithm, do not accommodate control constraints. This paper (Bagiev et al., 2007b) provides details of the development of a predictive algorithm and provides a number of examples showing the application of the approach to aggressive helicopter manoeuvres. The results show that the method can improve the realism of inverse simulation results for controlled manoeuvring flight. It is also believed that the approach could be helpful in the conceptual design of new vehicles and could also provide a basis for a trajectory generating algorithm. Such an algorithm could be useful in terrain following guidance aids such, as a "tunnel in the sky" system. It is clear that the methodology of predictive inverse simulation has potential value in other fields, such as robotics, underwater vehicles and automotive applications. These results are further supported by similar findings from the application of the receding horizon approach to a different set of aggressive manoeuvres in (Bagiev et al., 2007a – *supporting paper, [107]*).

Although the examples considered in the work reported in the two papers discussed in this section all relate to helicopter applications there is no reason why the predictive inverse simulation algorithm could not be applied equally well to problems in many other application areas. The approach has much in common with nonlinear predictive control.

6.3 Discussion

Inverse systems have provided a basis for much theoretical research in the control systems field over the past two decades and some significant applications have been reported by others. Despite the inherent difficulties in the mathematical methods needed for the nonlinear case, potential benefits in control applications are believed to be significant. Inverse simulation methods have potential advantages compared with classical methods of inversion in that they are applicable, with some restrictions in the case of non-minimum phase systems, to any model for which a forward simulation can be developed.

A number of control engineering applications of inverse simulation have been presented, some of which involve helicopter flight control problems while others involve the design and evaluation of feed-forward controllers for ship steering systems. The possible benefits of using inverse simulation methods for the design of combined feed-forward and feedback control systems, for cases where actuator saturation and other nonlinearities are significant, has been a topic of particular interest. The use of predictive control principles within the inverse simulation process is a recent area of research that has produced some promising possibilities for future work.

7. Sensitivity-Function Based Optimisation for Controller Tuning

7.1 Introduction

Computer-aided control system design techniques can lead to automatic control systems that give excellent performance when sufficient information is available about the system being controlled (the plant) and about the environment within which it operates. In real applications, whether in engineering or involving problems in the biomedical field, a mismatch always exists between the plant and the corresponding model used as the basis for system design. However, the effects of modelling errors and plant uncertainties can often be overcome, during commissioning of the system, through iterative tuning.

In the case of some commonly-used controllers, such as proportional, integral and derivative (PID) controllers, there are well-known and widely used procedures for tuning that can lead rapidly to a satisfactory performance. For most other forms of continuous and digital controller structures convenient tuning algorithms do not exist and, in practice, controller tuning often involves trial and error procedures. This can add significantly to the overall time for commissioning and thus to the overall cost of control system implementation. As the control system performance requirements become more demanding, the complexity of the resultant controller tends to increase. The extent to which controller parameters interact in terms of their effects on the overall system response also tends to increase with controller complexity. This usually leads to additional problems for those involved in on-site tuning.

7.2 Parameter Sensitivity Functions for Tuning Feedback Control Systems

Sensitivity functions offer valuable information for system design through providing a measure of a change in the system response that will result from changes in parameters of the system. The relative magnitudes of these sensitivity functions indicate which parameters are most significant in terms of their influence on system output variables. By selecting parameters that have the greatest effects on the steady state and dynamic performance of the system, the number of adjustable quantities can be kept to a minimum. If one knows the form of the desired response characteristics it is then possible to use sensitivity information to systematically improve the system performance.

Conventional approaches to the estimation of parameter sensitivity in closed-loop control systems (and also in other types of system that do not necessarily involve explicit feedback pathways) are mostly based on parameter perturbation methods or on the use of a sensitivity co-system (see, for example, (Tomović, 1963)). Perturbation methods involve calculation of differences between responses before and after changes of each adjustable parameter and thus, for p parameters, this process requires at least $2p$ separate tests. This approach also involves small differences between responses of similar magnitude and the results are likely to be adversely affected by measurement noise. Although the use of the sensitivity co-system approach reduces the number of tests to be carried out and, in the special case of single-input single-output linear systems, allows simultaneous estimation of all

parameter sensitivity functions from a single test, it does depend on precise *a priori* knowledge of the structure and parameters of the system. Such information is seldom available in practical control applications.

What is required for the tuning of parameters within the controller blocks of feedback systems is an approach that does not require *a priori* knowledge of the plant in the form of a detailed mathematical model and also avoids the need for large numbers of repeated tests, as is the case with parameter perturbation methods. Such an approach is provided by the so-called *signal convolution* method for the estimation of parameter sensitivities. The technique was developed initially for an application involving adjustment of synchronous generator excitation controllers in electrical power systems, but the approach has been shown to be applicable to many other problems involving closed-loop control.

7.2.1 A sensitivity function method for feedback controller tuning in multivariable closed-loop systems

For multivariable closed-loop systems described by the block diagram shown in Figure 7.1, a general method for controller tuning based on controller parameter sensitivity functions has been developed from results published in (El-Shirbeeny, Murray-Smith and Winning, 1974 – **submitted paper, [109])** and (Winning, El-Shirbeeny, Thomson and Murray-Smith, 1977 – *supporting paper, [110]*). These papers relate specifically to iterative tuning of single-input single-output voltage regulator systems.

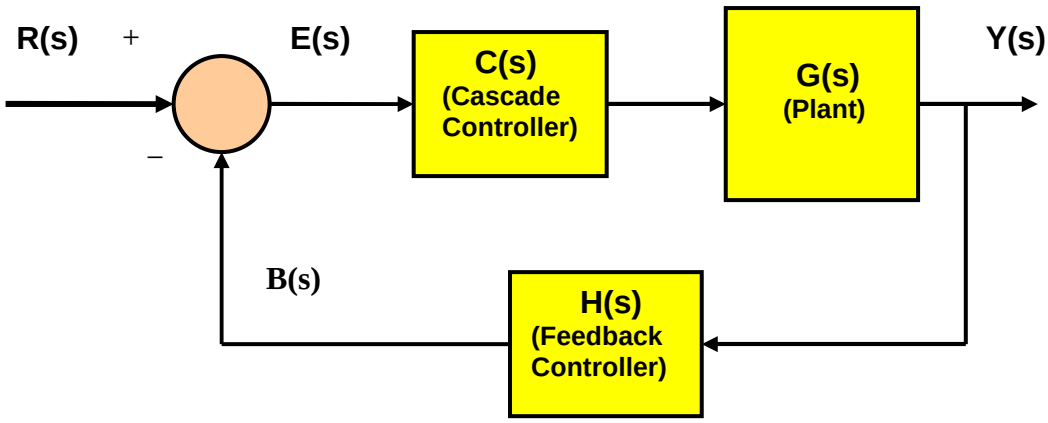

Figure 7.1: Block diagram of single-input single-output system with cascade and feedback controllers, where $R(s)$ represents the Laplace transform of the reference input $r(t)$ and $Y(s)$ represents the Laplace transform of the system output $y(t)$. The variables $e(t)$ and $b(t)$ correspond to the transformed variables $E(s)$ and $B(s)$ shown on the diagram.

The generalisation of this approach from the voltage regulator application to other forms of single-input single-output closed-loop system showed that the method avoids the need for explicit *a priori* information about the plant, provided the system

does not depart significantly from a linear mode of operation (Murray-Smith, 1986 - **submitted paper, [111]**).

In the multi-input multi-output case the block diagram is a straightforward multivariable system equivalent of the single-input single-output situation shown in Figure 7.1. The tuning algorithm allows predictions to be made of the effects of changes in parameters of the controller blocks ***C*** and ***H*** in the multivariable version of the diagram. Assume, first of all, that sensitivity functions $\partial \boldsymbol{y}(t)/\partial q_i$ for the response $\boldsymbol{y}(t)$ to variation of the parameter q_i of the cascade controller, ***C,*** or of the feedback controller ***H*** are available. It is possible then to express the difference between the desired response $\boldsymbol{y_d}(t)$ and the actual response $\boldsymbol{y}(t)$ by an equation of the form:

$$\boldsymbol{y}_d(t) = \boldsymbol{y}(t) + \frac{\partial \boldsymbol{y}(t)}{\partial \alpha_i}\Delta \boldsymbol{A} + \frac{\partial \boldsymbol{y}(t)}{\partial \beta_i}\Delta \boldsymbol{B} + \boldsymbol{R}_e(t) \tag{7.1}$$

where $\partial \boldsymbol{y}(t)/\partial \alpha_i$ and $\partial \boldsymbol{y}(t)/\partial \beta_i$ are the matrices of first order sensitivity functions of the system response $\boldsymbol{y}(t)$ to variation of the controller parameters α_i and β_i and $\boldsymbol{R}_e(t)$ is the residual error. The parameter vectors $\Delta \boldsymbol{A}$ and $\Delta \boldsymbol{B}$ in Equation (7.1) are defined as follows:

$$\Delta \boldsymbol{A} = [\Delta \alpha_1 \Delta \alpha_2 .....\Delta \alpha_n]^{\mathrm{T}} \tag{7.2}$$

where the quantities α_i are parameters of the cascade controller ***C*** and

$$\Delta \boldsymbol{B} = [\Delta \beta_1 \Delta \beta_2 .....\Delta \beta_n]^{\mathrm{T}} \tag{7.3}$$

where the parameters β_i are parameters of the feedback block ***H***.

In addition to reflecting the difference between the desired and actual responses of the model the quantity $\boldsymbol{R}_e(t)$ includes components associated with higher order parameter sensitivity functions which have been neglected.

Equation (7.1) shows clearly that it is possible to influence the residual error by adjusting the controller parameters and this allows minimisation of an appropriate cost function involving $\boldsymbol{R}_e(t)$. In the case of multi-input multi-output systems, the performance index to be minimised involves the sum of a number of distinct time histories because separate tests have to be carried out for each of the inputs (Murray-Smith, 1986 – **submitted paper, [111]**), (Manness & Murray-Smith, 1987 – *supporting paper, [112]*). Since there is an inherent approximation in the use of sensitivity functions in this way, the process of parameter adjustment is iterative. A number of different optimisation approaches have been used successfully in this work, including quasi-Newton methods which have been adopted for most of the applications reported in later sub-sections.

7.2.2 A signal convolution method for estimation of controller parameter sensitivity functions

In addition to direct estimation of parameter sensitivities by parameter perturbation, there are a number of ways, such as the sensitivity co-system approach of Tomović (1963), in which parameter sensitivity functions may be determined if there is a parametric model of the plant available. This process of sensitivity analysis becomes more difficult if no reliable plant model is available and this is a commonly encountered situation in practice.

The paper by (El-Shirbeeny, Murray-Smith & Winning, 1974 – **submitted paper, [109]**) established the foundation of an approach for estimation of controller sensitivity functions through simple iterative tests on the closed loop system and the application of signal processing techniques. The approach was extended to multivariable systems in the paper by (Murray-Smith, 1986 – **submitted paper, [111]**) and subsequent papers by (Manness & Murray-Smith, 1987 – *supporting paper, [112]*) and by (Gong, Oppen & Murray-Smith, 1995 – *supporting paper, [115]*) provide evidence of the effectiveness of this approach in a number of applications. A further publication in 2003 by (Murray-Smith, Kocijan & Gong, 2003 – **submitted paper, [116]**) brings together the main results of this research and compares the approach with the *iterative feedback tuning* method of Hjalmarsson (2002).

For multivariable systems having the feedback structure shown in Figure 7.1 involving a plant transfer function matrix $\boldsymbol{G}(s)$, a cascade controller transfer function matrix $\boldsymbol{C}(s)$ and a transfer function matrix in the feedback path $\boldsymbol{H}(s)$, it can be shown that

$$\boldsymbol{y}(s) = \left(\boldsymbol{I} + \boldsymbol{G}(s)\boldsymbol{C}(s)\boldsymbol{H}(s)\right)^{-1}\boldsymbol{G}(s)\boldsymbol{C}(s)\boldsymbol{r}(s) = \boldsymbol{W}(s)\boldsymbol{r}(s) \tag{7.4}$$

where $\boldsymbol{W}(s) = \left(\boldsymbol{I} + \boldsymbol{G}(s)\boldsymbol{C}(s)\boldsymbol{H}(s)\right)^{-1}\boldsymbol{G}(s)\boldsymbol{C}(s)\boldsymbol{r}(s)$ is the transfer function matrix of the closed-loop system. If the cascade and feedback controllers then depend on a set of adjustable parameters $\boldsymbol{q}$ it may be shown, for a given parameter q_i , that

$$\frac{\partial \boldsymbol{y}(s)}{\partial q_i} = \boldsymbol{G}(s)\frac{\partial \boldsymbol{C}(s)}{\partial q_i}\boldsymbol{e}(s) - \boldsymbol{G}(s)\boldsymbol{C}(s)\boldsymbol{H}(s)\frac{\partial \boldsymbol{y}(s)}{\partial q_i} - \boldsymbol{G}(s)\boldsymbol{C}(s)\frac{\partial \boldsymbol{H}(s)}{\partial q_i}\boldsymbol{y}(s) \tag{7.5}$$

In cases where the parameter q_i is a parameter α_i of the cascade controller it may be shown that

$$\frac{\partial \boldsymbol{y}(s)}{\partial \alpha_i} = \boldsymbol{W}(s)\boldsymbol{C}^{-1}(s)\frac{\partial \boldsymbol{C}(s)}{\partial \alpha_i}\boldsymbol{e}(s) \tag{7.6}$$

and when the parameter q_i is a parameter β_i of the cascade controller

$$\frac{\partial \boldsymbol{y}(s)}{\partial \beta_i} = -\boldsymbol{W}(s)\frac{\partial \boldsymbol{H}(s)}{\partial \beta_i}\boldsymbol{y}(s) \tag{7.7}$$

Hence the output sensitivities can, in both cases, be expressed as a product of the closed-loop system transfer matrix $\boldsymbol{W}(s)$ and a sensitivity vector $\boldsymbol{Z}_{qi}(s)$ so that:

$$\frac{\partial \boldsymbol{y}(s)}{\partial q_i} = \boldsymbol{W}(s)\boldsymbol{Z}_{qi}(s) \tag{7.8}$$

This sensitivity vector has the form:

$\boldsymbol{Z}_{\boldsymbol{qi}}(s) = [\boldsymbol{C}(s,\alpha)]^{-1}\frac{\partial \boldsymbol{C}(s,\alpha)}{\partial \alpha_i}\boldsymbol{e}(s)$ for the case of a cascade controller parameter and $\boldsymbol{Z}_{\boldsymbol{qi}}(s) = -\frac{\partial \boldsymbol{H}(s,\beta)}{\partial \beta_i}\boldsymbol{y}(s)$ for a feedback controller parameter. Hence, if the closed-loop transfer function can be estimated, it is clear that the sensitivity functions may be found by applying signals $\boldsymbol{e}(s)$ and $\boldsymbol{y}(s)$, which are both available within the system itself, to filters that have forms that depend only on the cascade controller transfer function matrix or on the feedback path transfer function matrix. These filters are independent of the plant transfer function matrix $\boldsymbol{G}(s)$.

The closed-loop system transfer function matrix $\boldsymbol{W}(s)$ may be estimated directly using unit impulse or unit step signals applied at the reference input. In the case of a reference input test signal which approximates a unit impulse Equation (7.8) becomes:

$$\frac{\partial \boldsymbol{y}(s)}{\partial q_i} = \boldsymbol{y}(s)\boldsymbol{Z}_{qi}(s) \tag{7.9}$$

For a reference input test signal in the form of a unit step Equation (7.8) takes the form:

$$\frac{\partial \boldsymbol{y}(s)}{\partial q_i} = s\boldsymbol{y}(s)\boldsymbol{Z}_{qi}(s) \tag{7.10}$$

In both cases the sensitivity signal vectors $\boldsymbol{Z}_{qi}(s)$ may be found by applying the error signal $\boldsymbol{e}(s)$ or the output $\boldsymbol{y}(s)$ to filters $\boldsymbol{F}_{qi}(s)$ which have a structure and parameters that depend only on $\boldsymbol{C}(s)$ or $\boldsymbol{H}(s)$. This is illustrated in the block diagram of Figure 7.2 which is, again, shown in single-input single-output form for reasons of clarity.

In the case of a parameter of the cascade controller block $\boldsymbol{C}(s)$ we have

$$\boldsymbol{F}_{qi}(s) = \boldsymbol{C}^{-1}(s)\frac{\partial \boldsymbol{C}(s)}{\partial \alpha_i} \tag{7.11}$$

and, for a parameter of the feedback block $\boldsymbol{H}(s)$

$$\boldsymbol{F}_{qi}(s) = -\frac{\partial \boldsymbol{H}(s)}{\partial \beta_i} \tag{7.12}$$

Transformation of Equation (7.9) and Equation (7.10) to the time domain is straightforward and gives, in the case of Equation (7.9)

$$\frac{\partial \boldsymbol{y}(t)}{\partial q_i} = \int_0^t \boldsymbol{y}(\tau)\boldsymbol{z}_{qi}(t-\tau)\mathrm{d}\tau \tag{7.13}$$

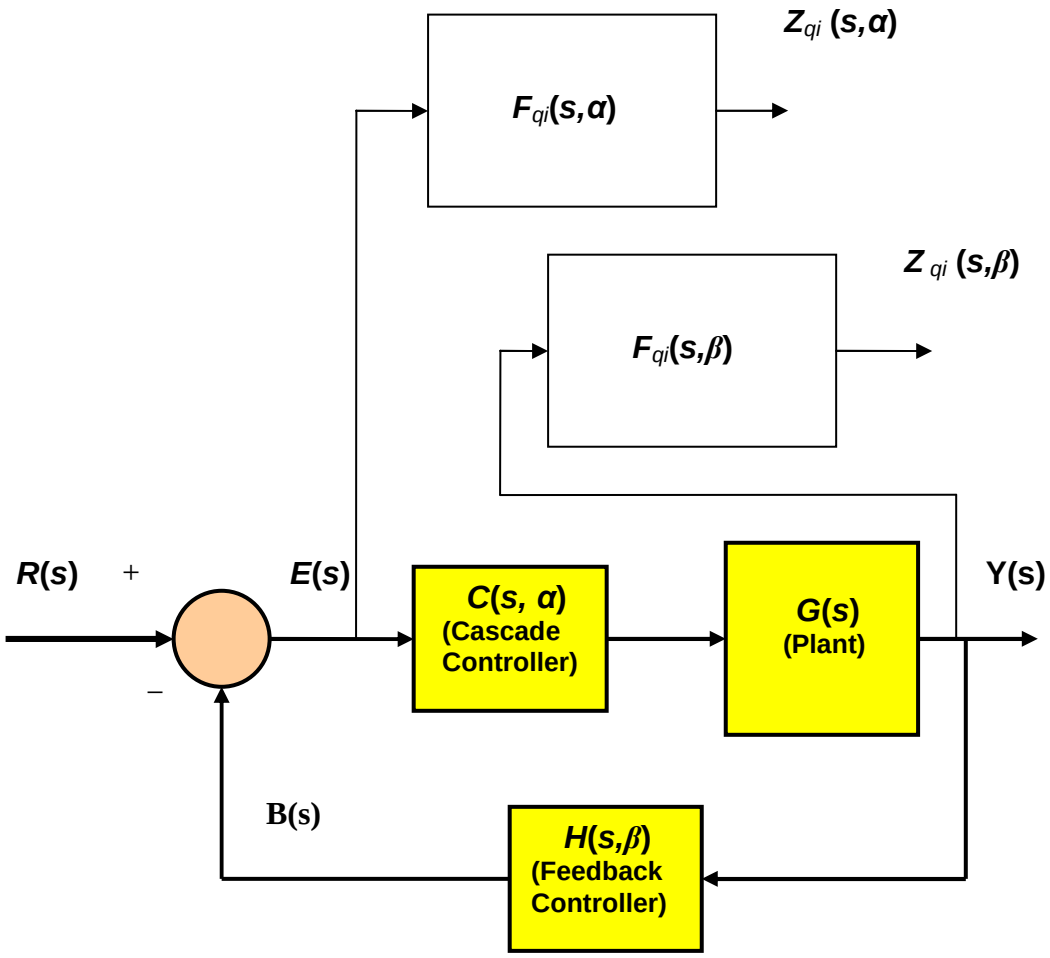

Figure 7.2: Block diagram for single-input single-output case showing method of generation of the sensitivity signals for one parameter of the cascade controller and one parameter of the feedback controller. Additional parameters can be handled by introducing extra sensitivity filters in parallel with each of the two sensitivity filters shown in this diagram.

In the case of Equation (7.10) the vector $\boldsymbol{y}(t)$ is simply replaced by its derivative with respect to time. Several different numerical techniques are available for calculation of a convolution integral of this kind in the time domain.

The approach may also be applied using the relevant equations directly in the frequency domain. This is discussed further in the 1986 paper by (Murray-Smith, 1986 – **submitted paper, [111]**). The experimental estimation of controller

sensitivity functions in the frequency domain, using broad-band signals applied at the reference input, is described in a paper by (Gong, Oppen & Murray-Smith, 1995 – *supporting paper, [115]*).

The paper by (Gong, Oppen & Murray-Smith, 1995 – *supporting paper, [115]*) also presents the theory for the signal convolution approach when applied to a digital control system. The approach adopted there uses a conventional system structure involving idealised representations of the analogue-to-digital and digital-to-analogue conversion processes. In this case z-transform analysis is used to show that the sensitivity functions may be found directly by simple arithmetic operations on the sampled variables at the output, at the summing element in the feedback path and at the outputs of the sensitivity filters. Once again it is demonstrated that the sensitivity functions for the parameters of the digital controller may be estimated entirely from measured response signals and calculations require no detailed information about the plant and its parameter values.

7.3 Applications of the Controller Tuning Method based on Sensitivity Functions Estimated using Signal Convolution.

There have been a number of different applications of the methods of controller tuning and sensitivity analysis based on signal convolution methods. Published accounts of applications to single input single output systems have included electrical power systems applications involving on-site adjustment of automatic voltage regulator systems (Winning, El-Shirbeeny et al., 1977 – *supporting paper, [110]*), and an application to a simulated aircraft flight control system (Murray-Smith, 1986 – **submitted paper, [111]**). Published applications to multi-input multi-output systems have included simulation studies for helicopter flight control and related handling qualities investigations (Manness & Murray-Smith, 1988a – *supporting paper, [113]*), (Manness & Murray-Smith, 1988b – *supporting paper, [114]*) and a detailed investigation of the application of the method two a two-input two-output laboratory system for liquid level control involving two coupled tanks (Murray-Smith, Kocijan & Gong, 2003 – **submitted paper, [116]**).

7.3.1 The signal convolution method applied to the tuning of a two-input two-output liquid-level control system

Figure 7.3 is a schematic diagram of a two-input two-output coupled tanks laboratory system. This system is a modified version of equipment available commercially (TecQuipment Ltd.). Changes made to the standard system involved replacement of resistive liquid level sensors by differential-pressure based depth sensors and the introduction of an additional pump to provide a flow input to the second tank. As outlined by (Murray-Smith, Kocijan & Gong, 2003 – **submitted paper, [116]**), the system may be described by a linearised state-space model

$$\begin{bmatrix} \dot{h}_1 \\ \dot{h}_2 \end{bmatrix} = \begin{bmatrix} \frac{-k_1}{a} & \frac{k_1}{a} \\ \frac{k_1}{a} & \frac{-k_1+k_2}{a} \end{bmatrix} \begin{bmatrix} h_1 \\ h_2 \end{bmatrix} + \begin{bmatrix} \frac{1}{a} & 0 \\ 0 & \frac{1}{a} \end{bmatrix} \begin{bmatrix} q_{i1} \\ q_{i2} \end{bmatrix} \tag{7.14}$$

where

$$k_1 = \frac{\sqrt{2g}C_{d1}a_1}{2\sqrt{H_1 - H_2}} \qquad \text{and} \qquad k_2 = \frac{\sqrt{2g}C_{d2}a_2}{2\sqrt{H_2 - H_3}}$$

and where a is the cross-sectional area of tank 1 and tank 2, a_1 is the total cross-sectional area of orifices linking the two tanks (with an associated discharge coefficient C_{d1}) and a_2 is the cross-sectional area of the outlet from tank 2 (with a discharge coefficient C_{d2}).

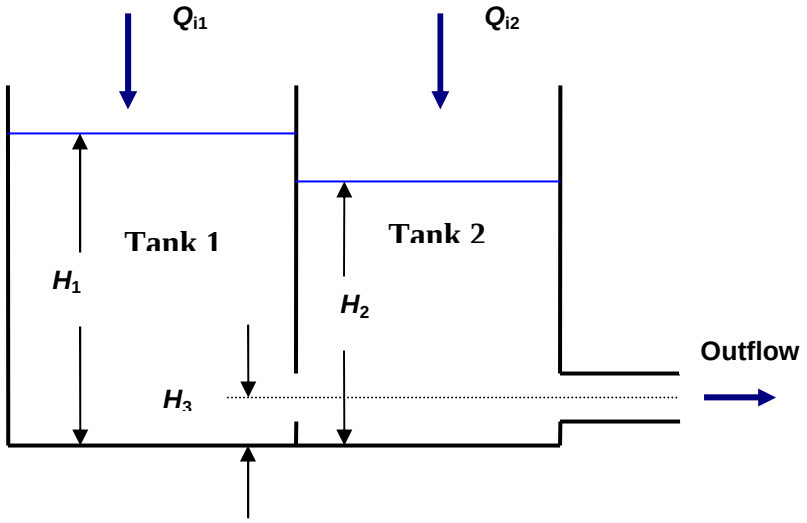

Figure 7.3: Schematic diagram of the coupled-tanks system showing the output variables H_1 and H_2 (corresponding to the variables h_1 and h_2 which, in the linearised equations, represent perturbations in the depths of liquid H_1 and H_2 in tanks 1 and 2 respectively) and the two input flow variables Q_{i1} and Q_{i2} (which correspond to the variables q_{i1} and q_{i2} in the linearised model). It should be noted that the quantity H_3 (and thus h_3 in the linearised representation) is a constant which represents the level of the centre point of the outflow pipe from tank 2.

Figure 7.4 shows a block diagram of the complete control system involving continuous proportional plus integral type controllers which have been designed to provide independent control of liquid level in the two tanks for operations about a selected steady state condition.

It should be noted that, because of the fact that tank 1 communicates only with tank 2 but tank 2 has an outlet, it is impossible for the system to operate in the desired fashion as a two-input two-output system with completely independent control of the two levels. Specifically, the design requirements cannot be satisfied if the steady state level for tank 2 is set to be greater than the demanded level for tank1. This is not a significant limitation since, for most practical operating requirements, the level in tank1 would be greater than the level in tank 2.

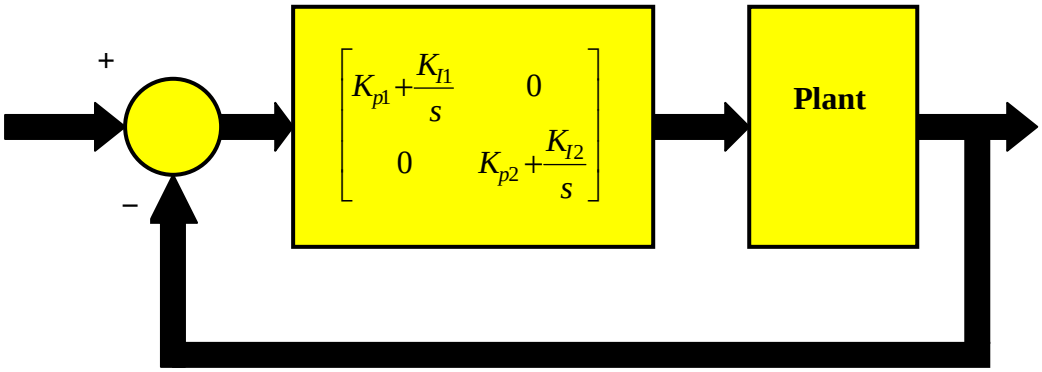

Figure 7.4: Structure of the liquid level control system showing the two-input two-output diagonal form of proportional plus integral controller.

Initial design values for the proportional and integral constants in the controller of Figure 7.4 were found by use of the individual channel analysis and design (ICAD) approach of O'Reilly and Leithead (1991). Tuning of the system by means controller parameter sensitivity functions found using the signal convolution approach, outlined above, was carried out successfully. Details of this work, including plots of the sensitivity functions estimated experimentally and the final form of control system transients may be found in (Murray-Smith, Kocijan & Gong, 2003 – **submitted paper, [116]**). Changes in the values of some parameters as a result of tuning were significant, with the proportional gains being altered by a factor of more than three in both loops. However, the number of iterations required to meet the design requirements, despite these large changes in parameters, was only three.

Experience gained with this application confirmed results found previously during studies involving the tuning of automatic voltage regulators in electrical power systems (Winning, El-Shirbeeny et al., 1977 – *supporting paper*, *[110]*), where the presence of significant measurement noise was not found to present difficulties for the numerical convolution approach. Although the sensitivity function estimates may be biased in situations with significant measurement noise, the results obtained from the two-tank system application show that the tuning process converges rapidly and produces system output responses which show small residual errors compared with the desired responses.

Although the technique is based entirely on linear theory, nonlinearities within the two-tank system resulting from fluid flow phenomena did not lead to difficulties although they do lead to large changes of the model parameters C_{d1} and C_{d2} for different operating conditions. The tuning process was found to be affected adversely by saturation of the pumps, but successful tuning could be achieved if the magnitudes of step or pulse test inputs were chosen to ensure that pump saturation did not occur.

The main benefit of using the signal convolution approach for the generation of the controller parameter sensitivity functions, compared with more traditional parameter perturbation methods, is that a minimum of two tests is needed (one for each

reference input) compared with a minimum of ten tests using parameter perturbations to generate the data for calculation of all eight sensitivity functions. This is due to the fact that, in the parameter perturbation approach, one test signal would have to be applied separately to each reference input with the unperturbed parameter settings and then four tests would have to be applied for each input for the four parameters perturbed individually. Results show that sensitivity functions found from the application of the signal convolution approach agree closely with corresponding results obtained using parameter perturbation (El-Shirbeeny, Murray-Smith & Winning, 1974 – **submitted paper [109]**), (Murray-Smith, Kocijan & Gong, 2003 – **submitted paper, [116]**).

7.3.2 Application of the controller tuning technique to helicopter flight control systems

Although helicopter flight mechanics models are steadily being improved in terms of their fidelity, limitations of these descriptions can still have a significant and degrading influence on the overall performance of flight control systems designed on the basis of such models. As the bandwidth requirements of flight control systems are extended to higher and higher frequencies in order to further enhance the agility and handling qualities of the vehicle, factors involving un-modelled or incorrectly modelled higher order dynamics continue to present difficulties. In particular, the effects of imperfect modelling of the dynamics of the main rotor, tail rotor and associated inflow dynamics and tip vortex phenomena commonly lead to requirements for retuning of the controller parameters following initial flight tests. Trial and error solutions do not provide cost effective solutions in terms of satisfying the demanding requirements of modern flight control systems and suffer from a lack of quantitative information about parameters to be adjusted and the amount by which they should be changed. Such an approach is certainly inadequate for the tuning of full authority fly-by-wire systems where the high level of system integration tends to obscure relationships between the overall system performance and the individual settings of adjustable parameters of the controller.

The technique developed for systematic tuning of helicopter flight control systems and described in the papers by Manness and Murray-Smith ((Manness & Murray-Smith, 1988a – *supporting paper, [113]*) and (Manness & Murray-Smith, 1988b – *supporting paper, [114]*)) relies on information provided by sensitivity functions. The signal convolution approach, outlined in Section 7.2.2 above, is ideal for the estimation of controller parameter sensitivity functions since this method does not require an accurate dynamic model of the vehicle. Flight testing is also kept to a minimum by the adoption of this approach but it is not feasible to carry out the tuning process in real time or even using a single test. Since helicopters are multi-input multi-output systems separate tests must be carried out involving the application of appropriate inputs perturbations to each channel of the multivariable control system in turn. Controller adjustments must therefore be made on the ground, between each set of flight experiments.

7.4 Discussion

Controller parameter sensitivity functions provide information which is potentially very useful for the purposes of control system tuning, especially at the system

commissioning stage. The iterative approach, being suggested here, is potentially attractive for practical industrial applications because it involves manual implementation of changes in controller parameter settings at each stage of the procedure. This allows those carrying out the tuning procedure to review results at each step in the light of their underlying knowledge of the system.

Methods for estimation of controller parameter sensitivity functions based on signal convolution lead to a single-stage time-domain procedure from data obtained from step or impulse response tests carried out on the closed-loop system. The approach does not require explicit *a priori* knowledge of the plant model and uses tests on the real system to generate a non-parametric description of the closed-loop system, in addition to the sensitivity functions for controller parameter tuning. The tuning process based on sensitivity functions converges rapidly and the computational demands in terms of numerical calculation of convolution integrals are not limiting for an off-line or semi-off-line tuning procedure. Implementation of the sensitivity filters for each adjustable parameter in the numerical convolution approach does not lead to significant additional problems since these filters have a relatively simple form for most controller transfer functions of practical importance.

The applications have allowed investigation of issues of convergence and robustness of the approach. Although the technique for calculation of controller parameter sensitivity functions is based on linear theory and, strictly speaking, is not applicable to systems with significant nonlinearities, practical experience with real applications suggests that this tuning method is remarkably reliable and robust. Applications involving physical systems, such as the voltage regulator system and the coupled tanks equipment, have shown that convergence of the tuning process was not adversely affect by the plant nonlinearities present. Issues of measurement noise have also been investigated extensively through those applications and measurement noise was not found to present any insuperable problems, provided appropriate signal conditioning filters are applied in the instrumentation and data collection systems (Murray-Smith, Kocijan & Gong, 2003 – **submitted paper, [116]**).

The approach must certainly be applied with caution if it is known that the plant has significant nonlinearities, such as saturation effects or other hard nonlinearities, within its normal operating range. Care must also be taken if significant levels of measurement noise are encountered during preliminary testing of the closed-loop system.

Results presented in the accompanying submitted papers and in the supporting publications show the significant practical benefits that can be obtained from the application of this approach to controller tuning. The applications considered are typical of many practical control problems and of the situations encountered during system commissioning tests that lead to a need for adjustments to parameters within controllers.

8 Related Work involving System Modelling and Control Applications

8.1 Other Contributions in System Modelling and Control

Further original contributions have been made in a number of areas. These include:

- Sensitivity analysis of linear closed-loop systems (especially in the context of pole placement techniques for feedback system design) (Murray-Smith, 2003c – *supporting paper, [117])*, (Murray-Smith, 2004b - *supporting paper, [118]*).
- Applications of established multivariable control system design methods to problems of helicopter flight control (Parry & Murray-Smith, 1985 – *supporting paper, [119]*),(Manness & Murray-Smith, 1992 – *supporting paper, [23]*), (Gribble, Manness & Murray-Smith, 1994 – *supporting paper, [24]*), (Gribble & Murray-Smith, 1990 – *supporting paper, [25]*), (Hughes, Manness & Murray-Smith, 1990 – *supporting paper, [26]*), (Manness, Gribble & Murray-Smith, 1990 – *supporting paper, [27]*).
- Control and simulation problems in systems involving single and multiple unmanned underwater vehicles (Mitchell, McGookin & Murray-Smith, 2003 – *supporting paper, [120]*), (Mitchell, McGookin & Murray-Smith, 2004 – *supporting paper,[121]*), (Carruthers, McGookin & Murray-Smith, 2005 – *supporting paper, [122]*), (Zenor, Murray-Smith, McGookin & Crosbie, 2009 – *supporting paper, [123]*).
- The design of observer systems for state estimation, fault detection and system reconfiguration in helicopters and autonomous underwater vehicles (Paterson & Murray-Smith, 1987 – *supporting paper, [124]*), (Mitchell, McGookin & Murray-Smith, 2004 – *supporting paper, [121]*).
- Biomimetic concepts and human factors aspects in control and robotics (Murray-Smith, 2003b – *supporting paper, [125]*), (Murray-Smith, 2005 – *supporting paper, [126]*).
- Methods for the quantitative investigation of neuronal activity (Downie & Murray-Smith, 1981 - *supporting paper, [127]*), (Olsen & Murray-Smith, 1993 - *supporting paper, [128]*), (Davey, Ellaway, Halliday, Murray-Smith & Rosenberg, 1986 - *supporting paper, [5]*), (Conway, Lau et al., 1990 – *supporting paper, [6]*), (Murray-Smith, Murray-Smith et al., 1995 – *supporting paper, [7]*).
- Implementation and experimental performance evaluation of fuzzy control systems for a pH neutralisation process (Ibrahim & Murray-Smith, 2007 – *supporting paper, [129]*).

Although none of the publications on these topics is included among the papers submitted as part of the work of this thesis, they are relevant since they provide information about some aspects of the broader context within which the research on system identification, modelling and system optimisation has been undertaken. Our publications relating to multivariable control system design techniques applied to helicopter flight control are especially relevant in this respect, as it was through that particular application that model quality and simulation model validation became one of my strong research interests.

8.2 Developments Relating to Education

Contributions have also been made to the field of system modelling and control through publications describing educational developments. Some of these are specifically concerned with engineering education, while others describe new developments in the use of dynamic system concepts, control and computer simulation methods in the education and training of students in physiology and medicine. Relevant examples, which can in many cases be linked to specific developments described elsewhere in this thesis, include:

- Presentation of basic ideas of mathematical modelling methods and computer simulation techniques for biologists together with case studies on applications of modelling in medicine (Pack & Murray-Smith, 1972 – *supporting paper, [130]*).
- Development of educational material relating more specifically to simulation and modelling in the teaching of respiratory gas exchange and respiratory control (Mills, Middleton et al., 1974 - *supporting paper, [131]*), (Carson & Murray-Smith, 1988 – *supporting paper, [132]*), (Murray-Smith & Carson, 1988a – *supporting paper, [133]*), (Murray-Smith & Carson, 1988b – *supporting paper, [134]*).
- Development of an educational case study on the modelling of muscle, muscle receptors and neuromuscular control (Murray-Smith & Zhao, 2007 – *supporting paper, [135]*).
- Development of a practical exercise on simulation model validation involving experimental and analytical work (Gong & Murray-Smith, 1998 – *supporting paper, [62]*).
- Development of a case study relating to the use of an aircraft lateral beam guidance system simulation in the teaching of control engineering (Murray-Smith, 1983 – *supporting paper, [136]*).
- Development of a case study involving use of a hydro-electric generator and governor system simulation in the teaching of control engineering (Murray-Smith, 1984 – *supporting paper, [137]*).
- Development of case studies on issues of model quality and inverse simulation, in the context of the teaching of integrated control system design concepts (Murray-Smith, 2003a – *supporting paper, [138]*), (Murray-Smith, 2004 – *supporting paper, [139]*).
- Preparation of two additional review papers, both dealing with biomedical engineering topics relating to aspects of the neuromuscular system ((Murray-Smith, Rosenberg & Rigas, 1987 – *supporting paper, [140]*), (Murray-Smith, 2006b – *supporting paper, [141]*).

9. Discussion and Overall Conclusions

The papers submitted in this thesis are strongly applications-oriented and this is believed to be one of the most important features of the work. The emphasis on applications has allowed situations to be considered where currently available techniques of system modelling and control system design have significant limitations and where developments of methodology could provide important benefits. The work described in the different sections of the thesis and the associated papers has explored some of these limitations and has provided evidence which may be of help to others in dealing with new applications or in moving towards new and more appropriate techniques for analysis or design for more highly integrated and complex systems. The combination of system modelling and control also serves to emphasise important links that should always exist between the processes of model development and the intended application of the model.

9.1 The System Modelling Aspects of the Research

The research on system modelling methods and applications emphasises the value of integrating system identification and parameter estimation techniques within a modelling approach based mainly on the application of physical laws and principles. Also, the research helps to demonstrate that some techniques which have attracted only specialist interest in the past, such as inverse simulation, have much to offer within the more general areas of model development and model validation. This is particularly important in dealing successfully with issues of model structure and structural uncertainties.

Issues of experimental design, which have for long been recognised as very important in system identification, are also important for other aspects of model development and especially in the external validation of simulation models. Assessing the adequacy of a model for a specific use is a difficult task and the problem of upgrading or tuning a model which is shown to be inappropriate for an intended application raises many questions which, ideally, should involve further experimentation or the use of available experimental data. Unfortunately, the whole area of assessment of model accuracy, model suitability for a specified application and external validation of models attracts relatively little attention in terms of research. Donald Rumsfeld's much quoted statement, made during a US Department of Defense news briefing (Rumsfeld, 2002) has direct relevance to the issues of model accuracy and uncertainties:

"… as we know, there are known knowns; there are things we know we know. We also know there are known unknowns; that is to say we know there are some things we do not know. But there are also unknown unknowns - the ones we don't know we don't know".

His statement has been much ridiculed and took the UK Plain English Campaign's award for the most baffling remark by a public figure later in the same year, but those words could certainly be applied to the processes of developing models. The "unknown unknowns" in modelling are among the most important things that have to be exposed by testing and by the whole process that we describe as "model validation".

Use of the term “validation” may itself give a false impression of model capabilities. Terms such as “model testing” or “model evaluation” are really more appropriate. They reduce the possibility of false confidence being built into model-based predictions just because the model involved has been subjected to some form of “validation”. Theories can be proved to be wrong but cannot ever be proved to be right. Thus, models that can be shown to provide accurate predictions of reality in some circumstances cannot be assumed to be capable of giving good predictions in all cases. The “unknown unknowns” mean that there can never be a simple conclusion in the processes that we conventionally call “model validation”.

A second important feature of the papers included in the thesis is that they discuss modelling and control applications from a variety of areas, including physiology, electro-optics and rotorcraft dynamics, as well as more traditional control engineering areas such as ships, underwater vehicles and electrical power generation systems. The benefits of a cross-disciplinary approach in system modelling are believed to be very significant. The value, in terms of cross-fertilisation of ideas resulting from involvement in a wide range of applications, can be seen from the detailed content of these papers. Although the fields of neurophysiology, respiratory gas exchange processes, electro-optic sensor-systems, helicopter flight mechanics, hydro-electric power generation and surface ship or underwater vehicle control may appear, initially, to have little in common, closer examination shows that systems from these different fields present many similar difficulties in terms of accurate modelling. The papers included in the thesis show that, in addition to displaying significant nonlinear behaviour, most credible models of such systems involve significant uncertainties in the early stages of their development. Important simplifications may also have to be introduced, often for reasons of computational complexity, if the model is to be useful for an application such as non-invasive measurement, a real-time system simulator or the design of an automatic control system.

One recurring theme that is important in the modelling work is the additional insight that can be gained through the dual use of time-domain and frequency-domain information. One example of this is the importance of coherence information in establishing the existence of linear or nonlinear relationships between variables. This has proved to be of considerable value, both in the experimental investigation of neuromuscular systems and in the identification of helicopter models from flight test data. Frequency-domain techniques have also proved useful for the reduction of high-order multi-input multi-output models.

Inverse systems also receive significant attention in the thesis. Inverse simulation methods, developed initially for use in handling-qualities studies for fixed-wing aircraft and helicopters, have been shown to provide important insight in modelling and simulation of complex systems of a more general kind. One aspect of this is the different physical insight that can result from examining the input needed to allow a specific form of output to be achieved. This is vitally important in actuator design and it is believed that the examples from the ship steering area show very clearly the benefits that inverse simulation can provide in assessing the effects of control surface limitations on performance.

Similar issues of robustness of the tools that are currently available arise in considering the routine use of evolutionary methods for system modelling. Genetic

algorithms offer a potentially important element of automation for optimisation procedures, both for model development and for design. However, such methods are at the stage where they could only be applied routinely in an industrial design environment if there was a significant period of training for those involved.

The use of genetic programming for system modelling applications has certainly led to interesting results in a number of applications considered in the papers within this thesis, but it is also clear that this is still very much a research area. Although it was concluded from the research reported in the papers on this topic that genetic programming methods were useful for the identification of the structure of nonlinear dynamic models, the success of the approach depended critically on the selection of appropriate functions for the function library. This requires good understanding of the likely physical phenomena in the system under investigation and therefore does not, in any way, imply a fully automated approach. Examples of prior knowledge that can be helpful in establishing the elements needed in the function library and the initial form of model include the following: first estimates of the order of the model, first estimates of the forms of nonlinearity most likely to be involved, known interactions between variables of the system and the form and limitations of existing models of similar systems. It is also important for the investigator to have an understanding of the availability of experimental data, the limitations of experimental design and the possibility that the resulting experimental data could be unevenly distributed over the operating range.

The role of the investigator is still vitally important and interaction between the user and the evolutionary optimisation tools is essential at various stages. Similar conclusions can be reached in the context of artificial neural networks and the closely associated methods involving local model networks. Here factors such as the choice of sub-models, the number of hidden layers and the number of neurons in a neural network, the choice of learning rates and other factors have to be chosen by the user, mostly on the basis of previous experience. Indeed, virtually all methods of system modelling involve issues of this kind where manual intervention by the user is essential.

In some cases this may involve the selection of parameters which are essentially “fiddle factors”, whereas in others the manual process involves more fundamental choices. In many cases, however, the reason for undertaking these procedures manually is associated with the fact that available algorithms for the more automated aspects of the system identification and model development process are not sophisticated enough to carry out the necessary additional optimisation. In other cases the objectives of this further level of optimisation cannot even be expressed in a sufficiently simple fashion. In many applications constraints have to be considered and there may also be a number of different objectives that have to be satisfied simultaneously. Trial and error procedures can be very tedious and also introduce additional subjective aspects to the modelling process. This is clearly an area in which additional research is necessary, aimed at developing techniques that lead to an improved interface between the computer user, the model being developed and the available system identification and optimisation tools.

It is generally accepted that an integrated approach to design should, ideally, involve use of generic forms of description and re-usable sub-models. Established examples of such a generic modelling approach can be found in application areas such as

automotive engineering (Sayers & Han, 1995) and gas turbines (Visser & Broomhead, 2000) as well in as the generic electro-optic sensor system model which is discussed in Section 4 and presented in more detail in (Smith, Murray-Smith & Hickman, 2007a – **submitted paper [46]**). Object-oriented methods are relevant for this and it is suggested that appropriate software environments may offer significant advantages for the development of re-usable and readily extendable models.

Block diagrams and flow graphs have for long been used to describe the processes of system modelling, including the processes involved in the application of system identification and parameter estimation techniques. It is therefore appropriate to conclude this sub-section with the construction of a diagram that attempts to bring together some of the factors that are particularly emphasised in this thesis, including prior knowledge, experimental design, model optimisation and external validation.

The most important fact about the system modelling process is that, when properly applied, it is an iterative procedure that involves development, testing and refinement. Figure 9.1 represents an attempt to incorporate the main steps involved in this cyclic process. The blocks associated with the real system and system test data are shown in yellow while steps concerned directly with the model are represented by pale blue blocks. Blocks that represent the processes of external validation and decisions on the adequacy of a model for the intended application are shown in pale green. Other blocks concerned with defining the purpose of the model, the intended application and the vitally important process of model documentation have no background colour.

What is particularly attractive about this particular form of diagram is that it emphasises the vitally important role of external validation and the importance of prior knowledge about the real system. If a model proves inadequate for the intended application when subjected to the rigorous processes of external validation, there is a possibility of correction through feedback. Feedback pathways lead not only to the blue blocks representing the model but also, through the block representing knowledge of the real system, to the yellow blocks involving experimental design and thus to further tests to collect additional data from the real system. The importance of documentation is also emphasised in the diagram and it must be noted that documentation must be put in place as soon as a model is approved for use in the intended application. The model documentation must be updated if, at any stage during its life cycle, the model has to be modified because of evidence that was not available when the initial positive decision was taken on its adequacy. The presence of the uppermost block in this diagram (involving definition of the modelling objectives and the application) also emphasises the fact that a model developed for one specific purpose cannot be used for another application without going through the whole process of external validation, testing and further refinement if necessary. It should be noted that the structure of Figure 9.1 applies to the development and assessment of inverse simulation models as well as to conventional models.

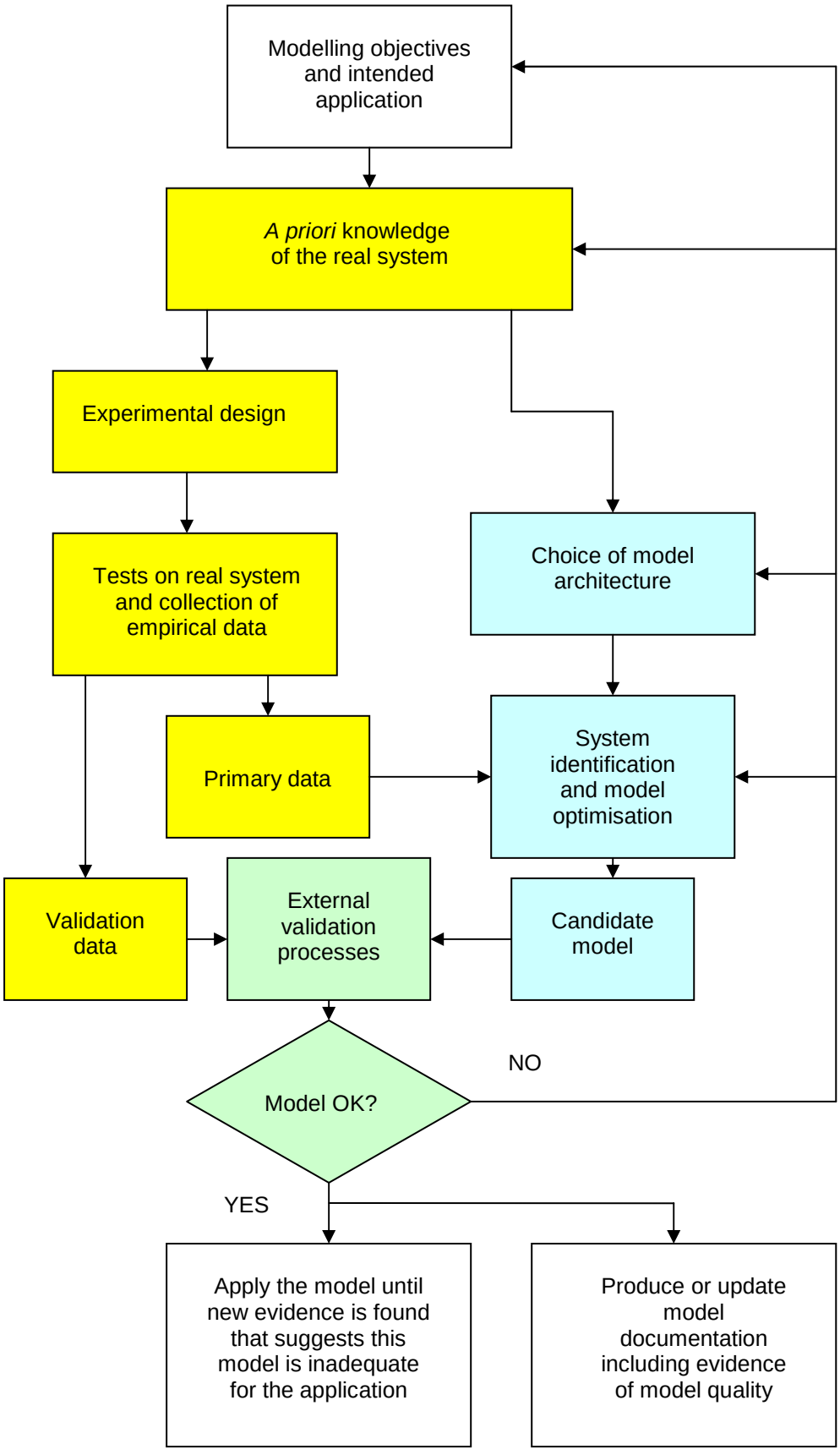

Figure 9.1: Block diagram of iterative processes of model development showing from formulation of modelling objectives to external validation and testing of model adequacy.

9.2 The Control Systems Aspects of the Research

Optimisation methods are particularly important in control systems that involve significant nonlinearity, either within the plant or within the controller. Particular emphasis has been placed in this thesis on sliding-mode controllers and their design using evolutionary techniques, together with research involving the application of other forms of advanced optimisation method, such as simulated annealing.

Results obtained from the work on sliding-mode control systems are very encouraging. The conventional approach to sliding-mode control system design involves manual adjustment of controller parameters within a simulation. That approach is very time-consuming and relies very much on the qualitative judgement and experience of the designer. The automated approach involving evolutionary techniques has been found to give reliable solutions in a reasonable period of time.

Other developments in terms of sliding-mode control methods have been associated with the successful introduction and practical application of “soft switching” techniques to eliminate problems associated with chattering in conventional forms of sliding-mode controller. While beneficial in improving robustness, the switching term in a sliding-mode system can cause oscillations of the control input which result in unwanted wear within the actuators. The soft-switching approach that has been adopted to avoid this problem involves use of a continuous hyperbolic tangent function instead of the discontinuous sign function of conventional switching-mode systems. In one application a soft switching sliding mode control system for ship navigation and propulsion has been tested using a hardware implementation of the controller as well as through computer simulation. The parameters of the control structure were adjusted to optimise performance using the genetic algorithm approach and the robustness was evaluated in the presence of environmental disturbances. The performance was found to be satisfactory and the results from hardware testing were entirely consistent with those found from simulation. Investigations of robustness for other ship control system applications through computer simulation studies, involving factors such as changes of loading and increased forward speed, have provided results that demonstrate good performance of sliding-mode systems for significant changes of operating condition.

Inverse simulation methods have also been examined closely in terms of their potential for control systems design in place of analytical inverse models which can present difficulties in the nonlinear case. Applications to problems involving the design of combined feedback and feed-forward control systems for ship steering applications have shown very encouraging results. This is believed to be a particularly important and promising development.

Techniques for the tuning of feedback systems, based on the on-line estimation of parameter sensitivity functions, have been shown to provide a viable approach to the on-line optimisation of closed-loop system performance during system commissioning tests. Tests on a variety of different systems have demonstrated the capabilities and potential of this approach.

9.3 Links between Modelling and Engineering System Design

One general point is that the complexity and detail of modern systems in some fields, such as in the defence and aerospace sectors, is beyond the level at which simple paper specifications seem appropriate. Although no systems of this complexity are considered in the papers in this thesis, other perhaps than the electro-optic sensor systems of Section 4, it is clear that conventional paper-based documentation and performance specifications have significant limitations. Some of these limitations are linked to the kind of errors to which humans are prone. In recent years there have been a number of well publicised examples from NASA, Airbus, BAE Systems and Boeing of complex systems that have failed or been seriously delayed because of design issues. These design problems often resulted from human errors, oversight or inappropriate specifications. Current limitations in conventional methods of documentation are referred to in the reviews of model validation methods (e.g., (Murray-Smith, 1998 – *supporting paper [56]*) and (Murray-Smith, 2006a – **submitted paper, [58]**)) and this is further emphasised by T.S. Ericsen of the US Office of Naval Research in the context of the design of highly complex power electronic systems. In a recent paper (2005), Ericsen states:

"…… *The model is the only vehicle capable of conveying the engineering details needed and flexible enough to be used in a true engineering design cycle. Moreover, the model is the only vehicle that has the potential for multi-physics relationships supporting integrated multi-discipline design. Thus the model must become the specification and simulation the design medium for future systems*"

Ericsen goes on to point out that today's modelling and simulation tools are primarily analysis tools and are not really designed for creativity and synthesis. The tools of the future will have to be more synergistic, with machines and designers working together. The machines would be handling large numbers of equations in a highly automated fashion, with the human designers monitoring solutions, observing trends and making jumps in terms of the overall design goals, on the basis of experience and inspiration. It is hoped that the methodological developments and accounts of successful applications in the areas discussed in this thesis, such as system identification and parameter estimation, inverse simulation, generic models, object-oriented simulation methods, model validation, and optimisation based on evolutionary methods can contribute in some small way to this long term objective.

One further important issue concerned with modelling and design relates to engineering education. Engineering students encounter mathematical modelling principles early in their university education and may also have met these ideas at an earlier stage, although the word "model" may not have been applied. However, they seldom have to consider what constitutes a good model and this issue is seldom discussed in introductory textbooks on modelling and simulation methods. Many students, therefore, lack an adequate understanding of the effects of modelling errors and uncertainties in design, since the emphasis usually given in undergraduate courses is on the formulation of models and on numerical methods of solution. Issues concerning accuracy and fitness for purpose need to be emphasised more. Students also need to be exposed to the iterative process of model development from the initial formulation stage, through simulation, internal verification, external validation and then back to the earlier stages for re-formulation and re-testing.

At a more specialised level, students in areas such as control engineering or aeronautics should also be exposed to multidisciplinary problems such as those arising in integrated flight control systems or in robotics. Group design projects involving students from different disciplines could provide valuable opportunities for an introduction to some of the more complex issues that can arise in multidisciplinary problem solving.

9.4 Areas for Further Research

Several research topics discussed in the papers included in this thesis provide areas of work in which further developments are required. In some cases, such as inverse simulation, the need is to take existing methods, which have been demonstrated successfully in a research environment, and translate them into robust and reliable tools for analysis and design that could be applied routinely by engineers in industry. Evolutionary methods of optimisation have also been highlighted as being important for modelling and system design optimisation applications, but existing computational tools tend to limit the routine applicability of these techniques to research and development types of environment.

A further area of this kind is helicopter system identification where it has been accepted by industry that system identification and parameter estimation methods have the potential to reduce the time required for flight testing within the processes leading to certification. This would reduce the development time and costs of new aircraft. However, because the currently available software tools lack robustness and require specialist knowledge in their use, those involved with new projects in industry are reluctant to make the investment of time and effort to ensure that their staff have the necessary expertise to apply identification or optimisation methods reliably.

Further development of software tools is therefore seen as being one of the main priorities for further, more general, acceptance of techniques outlined in this thesis. This suggestion is closely linked to the needs that are now emerging as a result of increased levels of design integration where currently available tools do not adequately handle all of the necessary technologies. For example, an understanding of how model approximations and uncertainties propagate through a highly integrated design is very complex but is also very important and justifies more investigation.

List of Original Contributions

Original papers, listed here using bold typeface, are included in full within the hard-copy version of this thesis. All submitted papers have been removed from this electronic version of the thesis due to Copyright restrictions. Reprints of most of those papers (and of many of the other original contributions) are available from the author on request (djms@elec.gla.ac.uk).

1. **C.G. Maclaine, P.N. McWilliam, D.J. Murray-Smith. and J.R. Rosenberg, 'A possible mode of action of static fusimotor axons as revealed by system identification techniques',** ***Brain Research*** **1977; 135: 351-357.**

2. **J.R.Rosenberg, D.J. Murray-Smith, D.J. and A. Rigas, 'An introduction to the application of system identification techniques to elements of the neuromuscular system',** ***Transactions of the Institute of Measurement and Control*** **1982; 4(2):187-201.**

3. **D.R. Halliday, D.J. Murray-Smith and J.R. Rosenberg, 'A frequency-domain identification approach to the study of neuromuscular systems - a combined experimental and modelling approach',** ***Transactions of the Institute of Measurement and Control*** **1992; 14(2):79-90.**

4. D.J. Murray-Smith and J.R. Rosenberg, 'Models of the muscle spindle: a case study in physiological system simulation'. In W. Ameling, Editor, *Proceedings of 1st European Simulation Congress ESC83*; Informatik-Fachberichte No. 71, 519-523, Berlin, Germany. Springer. 1983.

5. N.J. Davey, P.H. Ellaway, D.M. Halliday, D.J. Murray-Smith and J.R. Rosenberg, 'Comparative analysis of measures of association between spike trains', *Journal of Physiology* 1986, 377:14P.

6. B.A. Conway, J.W.N. Lau, D.J. Murray-Smith and J.R. Rosenberg, Techniques for the analysis of neuronal interactions, *Journal of Physiology* 1990; 429:5P.

7. D.J. Murray-Smith, E. Murray-Smith, J.R. Rosenburg and D. Junge, 'GAPTUTOR – A simulation-based tutorial introduction to methods of analysis of neuronal interactions'. In F. Breitenecker and I. Husinsky (Editors), *Proceedings EUROSIM'95*; 1329-1334, Amsterdam, The Netherlands. Elsevier Science. 1995.

8. G.J. Gray, D.J. Murray-Smith, Y.Li, and K.C. Sharman, 'Nonlinear system modelling using output error estimation of a local model network'. In *Proceedings of Society for Computer Simulation Summer Computer Simulation Conference (SCSC '96), Portland, Oregon, July 1996*; 460-465, San Diego, USA. Society for Computer Simulation. 1996.

9. A.I. Pack, B. Emery, F. Moran and D.J. Murray-Smith, 'Computer models of gas exchange processes in pulmonary ventilation'. In B. Wyke, Editor, *Ventilatory and Phonatory Control Systems*; 227-247, Oxford, UK. Oxford University Press.1974.

10. D. Murray-Smith and A. Pack, 'Techniques of computer simulation applied to respiratory gas exchange'. In D.E.M. Taylor and J.S. Whamond, Editors, *Non Invasive Clinical Measurement*; 186-202, London, UK. Pitman Medical. 1977.

11. **R.A. Bache, W.M. Gray and D.J. Murray-Smith, 'Time-domain identification applied to noninvasive estimation of cardiopulmonary quantities',** ***Proceedings IEE, Part D – Control Theory and Applications*** **1981; 128: 56-64.**

12. D.J. Murray-Smith, 'A review of respiratory system applications of computer simulation and modelling techniques'. In D. Möller, Editor, *Advanced Simulation in Biomedicine*; 83-116, New York, USA. Springer.1990.

13. R.A. Bache, and D.J. Murray-Smith, 'Structural and parameter identification of two lung gas exchange models'. In G.C. Vansteenkiste and P.C. Young, Editors, *Modelling and Data Analysis in Biotechnology and Medical Engineering*; 175-188, Amsterdam, The Netherlands. North Holland. 1983.

14. W.Greer, M.M. Jordan and D.J. Murray-Smith, 'A structural approach to respiratory control simulation'. In J.P.Paul, Editor, *Computing in Medicine*; 339-346, London, UK. Macmillan Publishers. 1982.

15. H. Thamrin and D. Murray-Smith, 'Modelling of the respiratory system for exercise conditions: a case study in physiological system simulation'. In B. Zupančič, R. Karba and S. Blažič, Editors, *Proc. EUROSIM 2007, 9-13 September 2007, Ljubljana, Slovenia*, Ljubljana, Slovenia. SLOSIM. 2007.

16. D.J. Murray-Smith, 'System identification and parameter estimation techniques in the modelling of physiological systems - a review'. In J.P.Paul, Editor, *Computing in Medicine*; 333-338, London, UK. Macmillan Publishers.1982.

17. **D.J. Murray-Smith, J.R. Rosenberg, D. Halliday and A. Rigas. 'The identification of a complex biological receptor'. In H.A. Barker, and P.C. Young, Editors,** ***Proceedings of the 7th IFAC/IFORS Symposium on Identification and System Parameter Estimation, York, 1985*****; 1595-1602, Oxford, UK, Pergamon Press, 1985.**

18. M.B. Dutia, D.J. Murray-Smith, J.R. Rosenberg and R. Wilson, 'The dependence of "driving" of Ia axons on muscle length and fusimotor stimulation frequency', *Journal of Physiology* 1977; 273: 30P-31P.

19. D.J. Murray-Smith. 'The development, validation and application of a simulation model of active skeletal muscle'. In J. Halin, W. Karplus and R. Rimane, Editors, *Proceedings CISS - First Joint Conference of International*

Simulation Societies, August 22-25 1994, Zürich, Switzerland; 600-604, La Jolla, USA. Society for Computer Simulation. 1994.

20. J.C. Jarvis, H. Gollee, M.M.N. Kwende, S. Salmons and D.J. Murray-Smith, 'Towards an optimized muscle controller'. In A. Pedotti, J. Quintern and R. Riener, Editors, *Neuroprosthetics*; 123-128, Berlin, Germany. Springer. 1996.

21. **H. Gollee, D.J. Murray-Smith and J.C. Jarvis, 'A nonlinear approach to modeling of electrically stimulated skeletal muscle',** ***IEEE Transactions on Biomedical Engineering*** **2001; 48(4): 406-415.**

22. **D.J. Murray-Smith, 'Modelling limitations for helicopter flight control system design'. In F. Breitenecker and I. Husinsky, I., Editors,** ***EUROSIM'95 Simulation Congress*****; 397-402, Amsterdam, The Netherlands. Elsevier. 1995.**

23. M.A. Manness. and D.J. Murray-Smith, 'Aspects of multivariable flight control law design for helicopters using eigenstructure assignment', *Journal of the American Helicopter Society* 1992; 37(3):18-32.

24. J.J. Gribble, M.A. Manness, and D.J. Murray-Smith, Helicopter flight control design: multivariable methods and design issues. In M.V. Cook, and M.J. Rycroft, editors, *Aerospace Vehicle Dynamics and Control*, pages 199-224, Oxford, UK. Clarendon Press. 1994.

25. J.J. Gribble and D.J. Murray-Smith, Command following control design by linear quadratic optimisation. In *Proceedings 16th European Rotorcraft Forum, Glasgow, Sept. 1990*; III.5.3.1-III.5.3.14, London, UK. Royal Aeronautical Society. 1990.

26. G. Hughes, M.A. Manness and D.J. Murray-Smith, 'Eigenstructure assignment for handling qualities in helicopter flight control law design'. In *Proceedings 16th European Rotorcraft Forum, Glasgow, Sept. 1990*; III.10.2.1-III.10.2.13, London, UK. Royal Aeronautical Society. 1990.

27. M.A. Manness, J.J. Gribble and D.J. Murray-Smith. 'Multivariable methods for helicopter flight control law design'. In *Proceedings 16th European Rotorcraft Forum, Glasgow, Sept. 1990*; III.5.2.1-III.5.2.14, London, UK. Royal Aeronautical Society. 1990.

28. G.D. Padfield, R. Thorne, D.J. Murray-Smith, C. Black and A.E. Caldwell, 'U.K. research into system identification for helicopter flight mechanics', *Vertica* 1987; 11(4): 665-684.

29. **C.G. Black. and D.J. Murray-Smith, 'A frequency-domain system identification approach to helicopter flight mechanics model validation',** ***Vertica*** **1989; 13: 343-368.**

30. **D.J. Leith, R. Bradley and D.J. Murray-Smith, 'Combination of data sets for system identification',** ***IEE Proceedings –Part D*** **1993; 140(1): 11-18.**

31. D.J. Murray-Smith, 'Modelling aspects and robustness issues in rotorcraft system identification'. In *AGARD Lecture Series 178: Rotorcraft System Identification (AGARD-LS-178)*; 7.1-7.9, Neuilly sur Seine, France. AGARD, 1991.

32. **D. Leith and D.J. Murray-Smith, 'Experience with multi-step test inputs for helicopter parameter identification',** ***Vertica*****1989; 13: 403-412.**

33. D.J. Leith and D.J. Murray-Smith, 'The design of energy and amplitude constrained optimal inputs for system identification', *Systems Analysis-Modelling-Simulation* 1993; 13(3-4): 209-238.

34. D.J. Murray-Smith, 'Identification methodologies: Flight test procedures'. In *AGARD Advisory Report 280: Rotorcraft System Identification (AGARD-AR-280)*; 51-57, Neuilly sur Seine, France. AGARD. 1991.

35. D.J. Murray-Smith and G.D. Padfield, 'Design of Experiments'. In *AGARD Lecture Series 178: Rotorcraft System Identification (AGARD-LS-178)*; 2.1-2.8, Neuilly sur Seine, France. AGARD. 1991.

36. D.J. Murray-Smith, 'Robustness issues'. In *AGARD Advisory Report 280: Rotorcraft System Identification (AGARD-AR-280)*; 213-222, Neuilly sur Seine, France. AGARD. 1991.

37. G.D. Padfield, and D.J. Murray-Smith, 'Identification results:- Case Study iii: Sa-330 Puma'. In *AGARD Advisory Report 280: Rotorcraft System Identification (AGARD-AR-280)*; 176-212, Neuilly sur Seine, France. AGARD. 1991.

38. **R. Bradley, C.G. Black and D.J. Murray-Smith, 'System identification strategies for helicopter rotor models incorporating induced flow',** ***Vertica*** **1989; 13: 281-293.**

39. D.J. Murray-Smith, 'The inverse simulation approach: a focused review of methods and applications', *Mathematics and Computers in Simulation* 2000; 53: 239- 247.

40. **Linghai Lu, D.J. Murray-Smith and D.G. Thomson, 'Sensitivity-analysis method for inverse simulation application',** ***AIAA Journal of Guidance, Control and Dynamics*** **2007; 30(1): 114-121.**

41. **Linghai Lu, D.J. Murray-Smith and D.G. Thomson. 'Issues of numerical accuracy and stability in inverse simulation',** ***Simulation Modelling Practice and Theory*** **2008; 16: 1350-1364.**

42. **D.J. Murray-Smith and Linghai Lu. 'Inverse simulation methods and applications'. In** ***Proceedings of Grand Challenges in Modeling and Simulation Conference, Edinburgh, June 2008*****, (one strand of** ***Summer Computer Simulation Multi-Conference*****), La Jolla, CA, USA, Society for Computer Simulation, 143-150. Omnipress. 2008.**

43. **D.J. Murray-Smith, Linghai Lu and E. W. McGookin. "Application of inverse simulation methods to a nonlinear model of an underwater vehicle". In *Proceedings of Grand Challenges in Modeling and Simulation Conference, Edinburgh, June 2008*, (one strand of *Summer Computer Simulation Multi-Conference*), La Jolla, CA, USA, Society for Computer Simulation, 135-141. Omnipress. 2008.**

44. **R. Bradley, G.D. Padfield, D.J. Murray-Smith and D.G. Thomson, 'Validation of helicopter mathematical models', *Transactions of the Institute of Measurement and Control* 1990; 12(4): 186-196.**

45. D.J. Murray-Smith and B.O.Wong, 'Inverse simulation techniques applied to the external validation of nonlinear dynamic models'. In P. Luker, Editor, *UKSim'97, Third Conference of the United Kingdom Simulation Society, Keswick, April 1997*; 100-104, Edinburgh, U.K., UKSim. 1997.

46. **M.I. Smith, D.J. Murray-Smith and D. Hickman, 'Mathematical and computer modeling of electro-optic systems using a generic modelling approach', *Journal of Defense Modeling and Simulation* 2007; 4(1): 3-16.**

47. **M.I. Smith, D.J. Murray-Smith and D. Hickman, 'Verification and validation issues in a generic model of electro-optic sensor systems', *Journal of Defense Modeling and Simulation* 2007; 4(1): 17-27.**

48. **M. Ostroversnik and D.J. Murray-Smith, 'Real modularity in dynamic system simulation languages', *Systems Analysis-Modelling-Simulation* 1998; 31(3): 169-182.**

49. **M. Ostroversnik and D.J. Murray-Smith, B Zupančič and S. Strmčnik. 'OO PHYSBE model – a benchmark for modular object-oriented dynamic system simulation tools'. In *Proceedings 3rd MATHMOD, Vienna, February 2-4, 2000*, Vol. 2; 595-598, Vienna, Austria. Argesim/ASIM. 2000.**

50. M.Ostroversnik and D.J. Murray-Smith, 'OOSlim – An experimental object oriented continuous simulation language'. In *Proceedings ERK'95, Portoroz, Slovenia, September 1995*. Vol A ; 285-288. 1995.

51. M. Ostroversnik and D.J. Murray-Smith, 'OOSlim'. In *Proceedings of 1996 European Simulation Symposium (ESS 96), October 1996, Genoa, Italy.* Ghent, Belgium. 1996.

52. D.J. Murray-Smith, 'A review of methods for the validation of continuous system simulation models'. In K.G. Nock, Editor, *Proceedings 1990 UKSC Conference on Computer Simulation*; 108-111, Burgess Hill, UK. United Kingdom Simulation Council. 1990.

53. D.J. Murray-Smith, 'Problems and prospects in the validation of dynamic models'. In A. Sydow, Editor, *Computational Systems Analysis 1992, Proceedings 4th International Symposium on Systems Analysis and Simulation, Berlin, Germany*; 21-27, Amsterdam, The Netherlands. Elsevier. 1992.

54. D.J. Murray-Smith, R. Bradley, and D.J. Leith, 'Identifiability analysis and experimental design for simulation model validation'. In F. Maceri and G. Iazeolla, Editors, *EUROSIM'92 Simulation Congress*; 15-20, Amsterdam, The Netherlands. North Holland. 1993.

55. D.J. Murray-Smith, 'Advances in simulation model validation: theory, software and applications'. In F. Breitenecker, and I. Husinsky, Editors, *Proceedings EUROSIM'95 Simulation Congress*; 75-84, Amsterdam, The Netherlands. Elsevier. 1995.

56. D.J. Murray-Smith, 'Methods for the external validation of continuous system simulation models', *Mathematical and Computer Modelling of Dynamical Systems* 1998; 4(1): 5-31.

57. D.J. Murray-Smith, 'Issues of model accuracy and external validation for control system design', *Acta Polytechnica* 2000; 40(3): 8-13.

58. **D.J. Murray-Smith, 'Simulation model quality issues in engineering: a review'. In I. Troch and F. Breitenecker, Editors, *Proceedings 5th MATHMOD, Vienna, February 2006*, Vienna, Austria. Argesim/ASIM. 2006.**

59. G.J. Gray, Lew Koi Voon and D.J. Murray-Smith, 'Applications of the distortion method for model validation'. In I. Troch and F. Breitenecker, Editors, *Proceedings 2nd MATHMOD VIENNA IMACS Symposium on Mathematical Modelling, February 1997*; 1033-1038, Vienna, Austria. Argesim.1997.

60. D.J. Murray-Smith, 'The validation of computer-based models in engineering: some lessons from computing science', *Acta Polytechnica* 2002; 41(4-5): 45-48.

61. H.Gollee and D.J. Murray-Smith, 'Validation of a local model network for electrically stimulated muscle'. In A.B. Bulsari and S. Kallio, Editors, *Neural Networks in Engineering Systems, Proceedings of the 1997 International Conference on Engineering Applications of Neural Networks (EANN'97)*; 191-194, Turku, Finland. Systems Engineering Association. 1997.

62. Mingrui Gong and D.J. Murray-Smith, 'A practical exercise in simulation model validation', *Mathematical and Computer Modelling of Dynamical Systems* 1998; 4(1): 100-117.

63. G.J. Gray and D.J. Murray-Smith. 'The external validation of nonlinear models for helicopter dynamics'. In R.J. Pooley and R.N. Zobel, Editors, *UKSS'93, Conference of the United Kingdom Simulation Society*; 143-147, Edinburgh, UK. United Kingdom Simulation Society. 1993.

64. **E.W. McGookin and D.J.Murray-Smith. 'Comment on "Nonlinear optimal tracking control with application to supertankers for autopilot design" by T. Çimen and S.P. Banks', *Automatica* 2006, 42: 2223-2225.**

65. **E. McGookin, D.J. Murray-Smith, Y. Li and T.I. Fossen, 'The optimization of a tanker autopilot control system using genetic algorithms', *Trans. Inst. Measurement and Control* 2000; 22: 141-178.**

66. A.Grant and D.J. Murray-Smith, 'Polygon imaging methods in plant monitoring and model validation applications', In *Proceedings Advanced Engineering Design 2004 Conference, Glasgow, September 2004*, Paper C1.07, Prague, Czech Republic.

67. **Mingrui Gong and D.J. Murray-Smith, 'Model reduction by an extended complex curve-fitting approach',** ***Transactions of the Institute of Measurement and Control*** **1993; 15(4): 188-198.**

68. **G.W. Bryce, T.R. Foord, D.J. Murray-Smith and P. Agnew, 'Hybrid simulation of water-turbine governors', In R.E. Crosbie and J.L. Hay, Editors,** ***Simulation Councils Proceedings Series*****; 6(1): 35-44, La Jolla, USA, Simulation Councils Inc.. 1976.**

69. **Y. Li, K.C. Ng, D.J. Murray-Smith, G.J. Gray and K.C. Sharman, 'Genetic algorithm automated approach to design of sliding mode control systems'.** ***International Journal of Control*** **1996; 63(4): 721-739.**

70. E.W. McGookin, D.J. Murray-Smith and Y.Li, 'A population minimisation process for genetic algorithms and its application to controller optimisation'. In *Proceedings, Second International Conference on Genetic Algorithms in Engineering Systems: Innovations and Applications, Glasgow 2-4 September 1997*, IEE Conference Publication 446, 79-85, London,UK. IEE. 1997.

71. E. Alfaro-Cid, E.W. McGookin and D.J. Murray-Smith, 'A novel non-uniform mutation operator and its application to the problem of optimising controller parameters', In *Proceedings Congress on Evolutionary Computation 2005*; 1555-1562, USA. IEEE. 2005.

72. **G.J. Gray, Y.Li, D.J. Murray-Smith and K.C. Sharman, 'Structural system identification using genetic programming and a block diagram oriented simulation tool',** ***Electronics Letters*** **1996; 32(15): 1422-1424.**

73. G.J. Gray, D.J. Murray-Smith, K.C. Sharman, and Y. Li. 'Nonlinear model structure identification using genetic programming'. In *Late-Breaking Papers of Genetic Programming '96 (GP '96), Stanford, California, July 1996*, 32-37. 1996.

74. G.J. Gray, D.J. Murray-Smith, Y.Li and K.C. Sharman, 'Nonlinear model structure identification using genetic programming'. In I. Troch and F. Breitenecker, *Proceedings 2nd MATHMOD VIENNA IMACS Symposium on Mathematical Modelling, February 1997*; 301-306, Vienna, Austria. Argesim. 1997.

75. G.J. Gray, T.Weinbrenner, D.J. Murray-Smith, Y.Li and K.C. Sharman, 'Issues in nonlinear model structure identification using genetic programming'. In *Proceedings, Second International Conference on Genetic Algorithms in Engineering Systems: Innovations and Applications, Glasgow 2-4 September 1997*, IEE Conference Publication No. 446: 308-313, London, UK. IEE. 1997.

76. **G.J. Gray, D.J. Murray-Smith, Y. Li, K.C. Sharman and T. Weinbrenner, 'Nonlinear model structure identification using genetic programming'. *Control Engineering Practice* 1998; 6: 1341-1352.**

77. K.C. Tan, Y. Li, D.J. Murray-Smith and K.C. Sharman, 'System identification and linearisation using genetic algorithms with simulated annealing'. In *Proceedings First IEE/IEEE International Conference on GA in Engineering Systems: Innovations and Applications, 12-14 September 1995, Sheffield, UK*; IEE Conference Publication No. 414: 164-169, London, UK, IEE. 1995.

.

78. E. Alfaro-Cid, E.W McGookin and D.J.Murray-Smith, 'Genetic algorithm optimisation of a supply ship propulsion and navigation systems'. In *Proceedings MTS/IEEE Oceans Conference, Honolulu (USA)*; 2645-2652, 2001.

79. **E.Alfaro-Cid, E.W. McGookin and D.J. Murray-Smith, 'GA-optimised PID and pole placement real and simulated performance when controlling the dynamics of a supply ship', *IEE Proceedings - Control Theory and Applications* 2006; 153(2): 228-236.**

80. Y. Li, K.C. Tan, K.C. Ng and D.J. Murray-Smith, 'Performance based linear control system design by genetic evolution with simulated annealing'. In *Proceedings 34th IEEE Conference on Decision and Control, New Orleans, LA, 13-15 December 1995*; 731-736, USA. IEEE. 1995.

81. E. Alfaro-Cid, E.W. McGookin and D.J. Murray-Smith, 'Optimisation of the weighting functions of an H^{∞} controller using genetic algorithms and structured genetic algorithms', *International Journal of Systems Science* 2008; 39(4): 335-347.

82. K.C. Ng, Y.Li, D.J. Murray-Smith and K.C. Sharman, 'Genetic algorithms applied to fuzzy sliding mode controller design', *Proceedings First IEE/IEEE International Conference on GA in Engineering Systems: Innovations and Applications, 12-14 September 1995, Sheffield, UK*; IEE Conference Publication No. 414: 536-542, London, UK. IEE. 1995.

83. **E. McGookin, D.J. Murray-Smith, Y. Li and T.I. Fossen, 'Ship steering control system optimisation using genetic algorithms', *Control Engineering Practice* 2000; 8: 429-443.**

84. **E. Alfaro-Cid, E.W. McGookin, D.J.Murray-Smith and T.I. Fossen, 'Genetic algorithms optimisation of decoupled sliding mode controllers: simulated and real results', *Control Engineering Practice* 2005; 13(6): 739-748.**

85. **E.W. McGookin and D.J. Murray-Smith, 'Submarine manoeuvring controllers' optimisation using simulated annealing and genetic algorithms', *Control Engineering Practice* 2006; 14(1): 1-15.**

86. E.W. McGookin, D.J. Murray-Smith, and Y Li, 'Submarine sliding mode controller optimisation using genetic algorithms. In *Proceedings UKACC*

International. Conference on Control, CONTROL'96, Exeter, September 1996: 424-429. London, UK. IEE. 1996.

87. M. Loo, E.W. McGookin and D.J. Murray-Smith, 'Sliding mode based inverse model control for oil tanker guidance'. In P.Horocek, M. Simandl and P. Zitek, Editors, *Preprints of the 16th IFAC World Congress, Prague, July 3-8, 2005*.

88. E.W. McGookin, D.J. Murray-Smith, Y. Li and T.I. Fossen, 'Parameter optimisation of a non-linear tanker control system using genetic algorithms'. In *Proceedings, Second International Conference on Genetic Algorithms in Engineering Systems: Innovations and Applications, Glasgow 2-4 September 1997*; IEE Conference Publication No. 446: 37-42, London, UK. IEE. 1997.

89. E.W. McGookin, D.J. Murray-Smith , Y.Li and T.I. Fossen, 'Non-linear tanker control system optimisation using genetic algorithms'. In *Proceedings Oceans'97 Conference MTS/IEEE, Halifax, Nova Scotia, Canada*; Volume 1: 17-22. 1997.

90. E. McGookin, D.J. Murray-Smith and T.I. Fossen. 'The use of genetic algorithms for nonlinear controller design'. *Acta Polytechnica* 2000; 40(3): 14-21.

91. E. Alfaro-Cid, E.W. McGookin and D.J. Murray-Smith, 'Genetic algorithm optimisation of an oil tanker control system'. In *Proceedings of the IFAC Conference on Control Applications in Marine Systems CAMD'01 Glasgow, U.K. July 2001*; 227-232.

92. G.J. Gray, Y.Li, D.J. Murray-Smith, E.Ronco and K.C. Sharman, 'The application of genetic algorithms to gain scheduling controller analysis and design'. In *Proceedings, Second International Conference on Genetic Algorithms in Engineering Systems: Innovations and Applications, Glasgow 2-4 September 1997*; IEE Conference Publication No. 446: 364-368, London, UK. IEE. 1997.

93. E. Alfaro-Cid, E.W. McGookin and D.J. Murray-Smith, 'Genetic algorithm optimisation of a ship navigation system', *Acta Polytechnica* 2001; 41(4/5): 13-19.

94. E.W. McGookin, D.J. Murray-Smith, and Y.Li, 'Segmented simulated annealing applied to sliding mode controller design'. In *Proceedings 13th World Congress of IFAC, San Francisco, USA, July 9-12, 1996*; Volume D: 333-338, IFAC. 1996.

95. G.J. Gray, Y. Li, D.J. Murray-Smith and K.C. Sharman, 'Specification of a control system fitness function using constraints for genetic algorithm based design methods'. In *Proceedings First IEE/IEEE International Conference on GA in Engineering Systems: Innovations and Applications, 12-14 September 1995, Sheffield, UK*; IEE Conference Publication No. 414: 530-535, London, UK. IEE, 1995.

96. E. Alfaro-Cid, E.W. McGookin, D.J. Murray-Smith and T.I. Fossen, 'Evolution of a strategy for ship guidance using two implementations of genetic programming'. In *Proceedings EuroGP 2005*; 3447: 250-260. 2005.

97. E. Alfaro-Cid, E.W. McGookin, D.J. Murray-Smith and T.I. Fossen, 'Genetic Programming for the automatic design of controllers for a surface ship', *IEEE Trans. On Intelligent Transportation Systems* 2008; 9(2): 311-321.

98. E. Alfaro-Cid, E.W. McGookin and D.J. Murray-Smith, 'A comparative study of genetic operators for controller parameter optimisation', *Control Engineering Practice* 2009; 17: 185-197.

99. A. Häussler, Y.Li, K.C. Ng, D.J. Murray-Smith and K.C. Sharman, 'Neurocontrollers designed by a genetic algorithm', *Proceedings First IEE/IEEE International Conference on GA in Engineering Systems: Innovations and Applications, 12-14 September 1995, Sheffield, UK*; IEE Conference Publication No. 414: 536-542,. London, UK. IEE. 1995.

100. **R. Simensen and D.J. Murray-Smith, 'Ship steering control by neural networks trained using feedback linearization control laws'. In J. Kocijan and R. Karba (Editors),** ***Preprints IFAC/IMACS International Workshop on Artificial Intelligence in Real-Time Control, Bled, Slovenia, Nov. 29-Dec. 1, 1995.***

101. M.A. Unar and D.J. Murray-Smith, 'Radial basis function networks for ship steering control'. *Proceedings 12th International Conference on Systems Engineering, ICSE'97, Coventry University, U.K., 9-11 September 1997*; 700-705.

102. **M.A. Unar and D.J. Murray-Smith, 'Automatic steering of ships using neural networks',** ***International Journal of Adaptive Control and Signal Processing*** **1999; 13: 203-218.**

103. **J. Kocijan and D.J. Murray-Smith, 'Robust nonlinear control for ship steering'. In N.E. Mastorakis, Editor,** ***Progress in Simulation, Modeling, Analysis and Synthesis of Modern Electrical and Electronic Devices and Systems*****; 235-240, World Scientific and Engineering Society Press. 1999.**

104. Linghai Lu, D.J. Murray-Smith and E. McGookin, 'Relationships between model inversion and inverse simulation techniques'. In I. Troch and F. Breitenecker, editors, *Proceedings 5th MATHMOD, Vienna, February 2006*, Vienna, Austria. Argesim/ASIM. 2006.

105. **L.Lu, D.J. Murray-Smith and E.W. McGookin, 'Investigation of inverse simulation for design of feedforward controllers',** ***Mathematical and Computer Modelling of Dynamical Systems*** **2007; 13(5): 437-454.**

106. **N. Cameron, D.G. Thomson and D.J. Murray-Smith, 'Pilot modelling and inverse simulation for initial handling qualities assessment',** ***Aeronautical Journal*** **2003; 107: 511-520.**

107. M. Bagiev, D.G. Thomson, D. Anderson and D. Murray-Smith, 'Adding realism to inverse simulation of helicopters in aggressive manoeuvring flight using a receding horizon approach', In *Proceedings American Helicopter Society Annual Forum, Virginia Beach, VA, May 1-3, 2007*, USA. American Helicopter Society. 2007.

108. **M. Bagiev, D.G. Thomson, D. Anderson and D. Murray-Smith, 'Hybrid inverse methods for helicopters in aggressive manoeuvring flight', In *Proceedings IFAC Symposium, Toulouse, 2007.* IFAC. 2007.**

109. **E.H.T. El-Shirbeeny, D.J. Murray-Smith and D.J.Winning, 'A technique for direct evaluation of parameter sensitivity functions', *Electronics Letters* 1974; 10(25/26): 530-531.**

110. D.J. Winning, E.H.T. El-Shirbeeny, E.C. Thompson and D.J. Murray-Smith, 'Sensitivity method for online optimisation of a synchronous generator excitation controller', *Proceedings IEE, Part D – Control Theory and Applications* 1977; 124: 631-638.

111. **D.J. Murray-Smith, 'Investigations of methods for the direct assessment of parameter sensitivity in linear closed loop control systems'. In S.G. Tzafestas and P. Borne, Editors, *Complex and Distributed Systems: Analysis, Simulation and Control*; 323-328, Amsterdam, The Netherlands. North Holland. 1986.**

112. M.A. Manness and D.J. Murray-Smith, 'Direct assessment of parameter sensitivity in multivariable closed-loop systems'. In R.N. Zobel, Editor, *Proceedings of 1987 UKSC Conference on Computer Simulation*; 149-153, Ghent, Belgium. Society for Computer Simulation. 1987.

113. M.A. Manness. and D.J. Murray-Smith, 'A technique for the tuning of helicopter flight control systems'. In *Proceedings 14th European Rotorcraft Forum, Milan, Sept. 1988*; 67.1-67.12, 1988.

114. M.A. Manness and D.J. Murray-Smith, 'A technique for the tuning of helicopter handling qualities'. In *Proceedings of International Conference on Helicopter Handling Qualities and Control, 15-17 November, 1988, London*; 26.1-26.16, London, UK. Royal Aeronautical Society. 1988.

115. M. Gong, I. Oppen and D.J. Murray-Smith, 'The development of tuning techniques for single-input single-output and multivariable control systems using controller sensitivity measures'. In R.C.H. Cheng and R.J. Pooley, Editors, *UKSS'95- Second Conference of the UK Simulation Society*; 73-79, Edinburgh, UK. United Kingdom Simulation Society. 1995.

116. **D.J. Murray-Smith, J. Kocijan and Mingrui Gong, 'A signal convolution method for estimation of controller parameter sensitivity functions for tuning of feedback control systems by an iterative process', *Control Engineering Practice* 2003; 11(9): 1087-1094.**

117. D.J. Murray-Smith, 'An approach to closed-loop system design and sensitivity analysis based on s-plane geometry'. In I. Troch and F.Breitenecker, Editors, *Proceedings of 4th MATHMOD Symposium, Vienna, February 2003*; 1456-1465, Vienna, Austria. Argesim. 2003.

118. D.J. Murray-Smith, 'Software for closed-loop system design and sensitivity analysis based on s-plane geometry and its use in the teaching of control engineering design principles', In *Proceedings Advanced Engineering Design 2004 Conference, Glasgow, September 2004*; Paper E1.07, Prague, Czech Republic. Orgit. 2004.

119. D.L.K.Parry and D.J. Murray-Smith, 'The application of modal control to the single rotor helicopter'. In *Proceedings of 11th European Rotorcraft Forum, London, September 1985*; 78.1-78.18. 1985.

120. A. Mitchell, E.W. McGookin and D.J.Murray-Smith, 'Comparison of control methods for autonomous underwater vehicles'. In *Proceedings of the 1st IFAC Workshop on Guidance and Control of Underwater Vehicles (GCUV2003), Newport, Wales*; 41-46. IFAC. 2003.

121. A.J. Mitchell, E.W. McGookin and D.J. Murray-Smith, 'Implementation of sliding mode observer based reconfiguration in an autonomous underwater vehicle', *Acta Polytechnica* 2005; 45(4): 18-24.

122. B. Carruthers, E.W. McGookin and D.J. Murray-Smith, Adaptive evolutionary search algorithm with obstacle avoidance for multiple UAVs. In P.Horocek, M. Simandl and P. Zitek, editors, *Preprints of the 16th IFAC World Congress, Prague, July 3-8, 2005*; IFAC. 2005.

123. J.J. Zenor, D.J. Murray-Smith, E.W. McGookin & R.E. Crosbie, 'Development of a multi-rate simulation model of an unmanned underwater vehicle for real-time applications'. In I. Troch and F. Breitenecker, Editors, *Proceedings MATHMOD 09, Vienna, February 9-13, 2009*; 1951-1957, Vienna, Austria, Argesim/Asim. 2009.

124. C.S. Paterson and D.J. Murray-Smith, 'Observers for state estimation and fault detection – a simulation study'. In R.N. Zobel, Editor, *Proceedings of 1987 UKSC Conference on Computer Simulation*; 174-180, Ghent, Belgium. Society for Computer Simulation. 1987.

125. D.J.Murray-Smith. 'Biological systems thinking for control engineering design', In *Proceedings Advanced Engineering Design 2003 Conference, Prague, June 2003*; Paper F5.5, Prague, Czech Republic. Orgit. 2003.

126. D.J. Murray-Smith, 'Biomimetic and human supervisory concepts for intelligent control'. In *Proceedings of International Conference on Intelligent Systems (ICIS2005),1-3 December 2005, Kuala Lumpur, Malaysia,* Plenary Lecture No. 1. Universiti Teknologi Petronas. 2005.

127. I.C. Downie and D.J. Murray-Smith, 'Simulation of systems involving pulse frequency modulation with special reference to modelling of muscle spindles'. In *Proceeedings 1981 UKSC Conference on Computer Simulation*, 143-152, Guildford, UK. Westbury House. 1981.

128. O.H. Olsen and D.J. Murray-Smith, 'Quantifying periodic activity in central pattern generators: the crayfish swimmeret', *Journal of Neuroscience Methods* 1993; 50: 25-35.

129. Rosdiazli Ibrahim and D.J. Murray-Smith, 'Design, Implementation and Performance Evaluation of a fuzzy control system for a pH neutralisation process pilot plant'. In *Proceedings of International Conference on Intelligent and Advanced Systems (ICIAS 2007), Kuala Lumpur, November 2007*; Kuala Lumpur, Malaysia. Universiti Teknologi Petronas. 2007.

130. A.I. Pack and D.J. Murray-Smith, 'Mathematical models and their applications in medicine', *Scottish Medical Journal* 1972; 17: 401-409.

131. R.J. Mills, S. Middleton, D.J. Murray-Smith, and A.I. Pack, 'Simulation in the teaching of concepts of respiratory gas exchange', *International Journal of Mathematics Education in Science and Technology* 1974; 5: 381-387.

132. E.R. Carson and D.J. Murray-Smith, 'The conceptual basis of modelling the respiratory system'. In D.G. Cramp and E.R. Carson, Editors, *The Respiratory System*; 1-12, London, UK. Croom Helm.1988.

133. D.J. Murray-Smith and E.R. Carson, 'The modelling process in respiratory medicine'. In D.G. Cramp and E.R. Carson, Editors, *The Respiratory System*; 296-333, London, UK. Croom Helm.1988.

134. D.J. Murray-Smith, and E.R. Carson, 'Case studies of respiratory system models'. In D.G. Cramp and E.R. Carson, Editors, *The Respiratory System*; 334-389, London, UK. Croom Helm.1988.

135. D.J. Murray-Smith and Siqi Zhao, 'A graduate-level multi-purpose educational case study on modelling and simulation of the neuromuscular system'. In B.Zupančič, R.Karba and S. Blažič, Editors, *Proceedings EUROSIM 2007, 9-13 September 2007, Ljubljana, Slovenia*; Ljubljana, Slovenia. SLOSIM. 2007.

136. D.J. Murray-Smith, 'Use of an aircraft lateral beam guidance system simulation in the teaching of control engineering'. In W. Ameling, Editor, *Proceedings of 1st European Simulation Congress ESC83*, Informatik-Fachberichte, No. 71; 337-342, Berlin, Germany. Springer. 1983.

137. D.J. Murray-Smith, 'Use of a hydro-electric generation system simulation in the teaching of control engineering'. In D.J. Murray-Smith, Editor, *Proceedings of the 1984 UKSC Conference on Computer Simulation, 12-14 September 1984,University of Bath*; 451-457, London, UK. Butterworth. 1984.

138. D.J.Murray-Smith, 'A case-study based approach to modelling and simulation education', In I. Troch and F. Breitenecker, Editors, *Proceedings 4th MATHMOD, Vienna, February 2003*; 295-302, Vienna, Austria. Argesim. 2003.

139. D.J. Murray-Smith, 'Issues of model quality and inverse simulation in introducing students to concepts of integrated control system design', In *Proceedings Advanced Engineering Design 2004 Conference, Glasgow, September 2004*; Paper E1.09, Prague, Czech Republic. Orgit. 2004.

140. D.J. Murray-Smith, J.R. Rosenberg and A. Rigas, 'Muscle spindle modelling and identification'. In M. Singh, Editor, *Systems and Control Encyclopedia*; 5: 3238-3242, Oxford, UK. Pergamon Press.1987.

141. D.J. Murray-Smith, 'Neuromuscular Systems'. In M. Akay, Editor, *Wiley Encyclopedia of Biomedical Engineering*, Paper 0839, Hoboken, N.J., USA. Wiley. 2006.

References

Note: Papers included in full within the hard-copy version of this thesis are highlighted using the * symbol.

Alfaro-Cid, E., McGookin, E.W. & Murray-Smith, D.J. (2001a) 'Genetic algorithm optimisation of an oil tanker control system'. In *Proceedings of the IFAC Conference on Control Applications in Marine Systems CAMD'01*, Glasgow, UK. July 2001, 227-232.

Alfaro-Cid, E., McGookin, E.W. & Murray-Smith, D.J. (2001b) 'Genetic algorithm optimisation of a ship navigation system'. *Acta Polytechnica*, **41**(4/5), 13-19.

Alfaro-Cid, E., McGookin, E.W. & Murray-Smith, D.J. (2001c) 'Genetic algorithm optimisation of a supply ship propulsion and navigation systems'. In *Proceedings MTS/IEEE Oceans Conference, Honolulu*, USA, IEEE, 2645-2652.

Alfaro-Cid, E., McGookin, E.W. & Murray-Smith, D.J. (2005) 'A novel non-uniform mutation operator and its application to the problem of optimising controller parameters'. In *Proceedings Congress on Evolutionary Computation 2005*. USA, IEEE, 1555-1562.

Alfaro-Cid, E., McGookin, E.W. & Murray-Smith, D.J. (2006) 'GA-optimised PID and pole placement real and simulated performance when controlling the dynamics of a supply ship'. *IEE Proceedings - Control Theory and Applications*, **153**(2), 228-236. *

Alfaro-Cid, E., McGookin, E.W. & Murray-Smith, D.J. (2008) 'Optimisation of the weighting functions of an H^{∞} controller using genetic algorithms and structured genetic algorithms'. *International Journal of Systems Science*, **39**(4), 335-347.

Alfaro-Cid, E., McGookin, E.W. & Murray-Smith, D.J. (2009) 'A comparative study of genetic operators for controller parameter optimisation'. *Control Engineering Practice*, **17**, 185-197.

Alfaro-Cid, E., McGookin, E.W., Murray-Smith, D.J. & Fossen, T.I. (2005a) 'Genetic algorithms optimisation of decoupled sliding mode controllers: simulated and real results'. *Control Engineering Practice*, **13**(6), 739-748.

Alfaro-Cid, E., McGookin, E.W., Murray-Smith, D.J. & Fossen, T.I. (2005b) 'Evolution of a strategy for ship guidance using two implementations of genetic programming'. In *Proceedings EuroGP 2005*, 250-260.

Alfaro-Cid, E., McGookin, E.W., Murray-Smith, D.J. & Fossen, T.I. (2008) 'Genetic Programming for the automatic design of controllers for a surface ship'. *IEEE Transactions on Intelligent Transportation Systems*, **9**(2), 311-321.

Amjad, A.M., Breeze, P., Conway, B.A, Halliday, D.M. & Rosenberg, J.R. (1989) 'A framework for the analysis of neuronal networks'. *Progress in Brain Research*, **80**, 243-255.

Anderson, J.H. (1967) ‘Geometrical approach to the reduction of dynamic systems’. *Proceedings Institution of Electrical Engineers*, **114**(7), 1014-1018.

Angers, D. & Delisle, G.Y. (1971) ‘A study of the action of static and dynamic fusimotor fibres with a mechanical model of the mammalian muscle spindle’. *IEEE Transactions on Biomedical Engineering*, **18**, 175-180.

Anonymous, (1991) *Rotorcraft System Identification.* AGARD Advisory Report 280 (AGARD-AR-280). Neuilly sur Seine, France, AGARD, September 1991.

Anonymous, (1994) *Aeronautical Design Standard ADS-33D. Handling qualities specifications for military rotorcraft*. US Army Aviation and Troop Command, St.Louis, Mo., Directorate for Engineering, July 1994.

Anonymous, (1995) *Technology Foresight: Progress through Partnership*, **12** (Defence and Aerospace), UK Office of Science and Technology, UK, HMSO.

Åström, K.J. & Bohlin, T. (1966) ‘Numerical identification of linear dynamic systems from normal operating records’. In P.H. Hammond, Editor, *Theory of Self-Adaptive Control Systems*. New York, USA, Plenum Press.

Atkinson, A.C. (1992) ‘A segmented algorithm for simulated annealing’, *Statistics and Computing*, **2**, 221-230.

Avenzini, G. (2001) ‘Two-timescale inverse simulation of a helicopter model’. *Journal of Guidance, Control and Dynamics*, **24**, 330-339.

Bache, R.A., Gray, W.M. & Murray-Smith, D.J. (1981) ‘Time-domain identification applied to noninvasive estimation of cardiopulmonary quantities’. *Proceedings IEE, Part D – Control Theory and Applications*, **128**(2), 56-64. *

Bache, R.A. & Murray-Smith, D.J. (1983) ‘Structural and parameter identification of two lung gas exchange models’. In G.C. Vansteenkiste and P.C. Young, Editors, *Modelling and Data Analysis in Biotechnology and Medical Engineering*. Amsterdam, The Netherlands, North Holland, 175-188.

Bacon, B.J. & Schmidt, D.K. (1988) ‘Fundamental approach to equivalent system analysis’. *J. Guidance, Control and Dynamics*, **11**(6), 527-534.

Bagiev, M., Thomson, D.G., Anderson, D. & Murray-Smith, D.J. (2007a) ‘Hybrid inverse methods for helicopters in aggressive manoeuvring flight’. In *Proceedings IFAC Symposium, Toulouse, 2007.* IFAC, 2007. *

Bagiev, M., Thomson, D.G., Anderson, D. & Murray-Smith, D. (2007b) ‘Adding realism to inverse simulation of helicopters in aggressive manoeuvring flight using a receding horizon approach’. In *Proceedings American Helicopter Society Annual Forum, Virginia Beach, VA, May 1-3, 2007*. USA, American Helicopter Society.

Bartlett, M.S. (1963) ‘The spectral analysis of point processes’. *Journal Royal Statistical Society*, **B25**, 264-280.

Beck, J.V. & Arnold, K.J. (1977) *Parameter Estimation in Science and Engineering.* New York, USA, Wiley.

Bellman R. & Åström, K.J. (1970) 'On structural identifiabilty'. *Mathematical Biosciences*, **7**, 329-339.

Bendat, J.S. & Piersol, A.G. (1980) *Engineering Applications of Correlation and Spectral Analysis*. New York, USA, Wiley.

Bendat, J.S. & Piersol, A.G. (2000) *Random Data: Analysis and Measurement Procedures.* 3rd Edition. New York, USA, Wiley.

Black, C. G. & Murray-Smith, D.J. (1989) 'A frequency-domain system identification approach to helicopter flight mechanics model validation'. *Vertica* , **13**(3), 343-368.*

Bradley, R., Black, C.G. & Murray-Smith, D.J. (1989) 'System identification strategies for helicopter rotor models incorporating induced flow'. *Vertica*, **13**(3), 281-293.*

Bradley, R., Padfield, G.D., Murray-Smith, D.J. & Thomson, D.G. (1990) 'Validation of helicopter mathematical models'. *Transactions of the Institute of Measurement and Control*, **12**(4), 186-196. *

Brillinger, D.R. (1972) 'The spectral analysis of stationary interval functions'. In L.M. Le Cam, J. Neyman and L.E. Scott, Editors, *Proceedings of 6th Berkeley Symposium on Mathematical Statistics and Probability.* Berkeley, USA, University of California Press, 483-513.

Brillinger, D.R. (1975a) 'The identification of point process systems', *Annals of Probability*, **3**, 909-929.

Brillinger, D.R. (1975b) 'Statistical inference for stationary point processes'. In M.I. Puri, Editor, *Stochastic Processes and Related Topics*, **1**. New York, USA, Academic Press, 55-79.

Brillinger, D.R. (1978) 'Comparative aspects of the study of ordinary time series and of point processes'. In P.R. Krishnaiah, Editor, *Developments in Statistics,* **1**. New York, USA, Academic Press, 33-134.

Brillinger, D.R., Bryant, H.C. Jr. & Segundo, J.P. (1976) 'Identification of synaptic interactions'. *Biological Cybernetics*, **22**, 213-228.

Brockett, R.W. 1965 'Poles, zeros and feedback: State space interpretation'. *IEEE Transactions on Automatic Control*, **10**, 129-135.

Brooks, R.R., Iyengar, S.S. & Chen, J. (1996) 'Automatic correlation and calibration of noisy sensor readings using elite genetic algorithms', *Artificial Intelligence*, **84**, 339-354.

Brovko, O., Wiberg, D.M., Arena, L. & Bellville, J.W. (1981) 'The extended Kalman filter as a pulmonary blood flow estimator". *Automatica*, **17**, 213-220.

Bryce, G.W., Foord, T.R., Murray-Smith, D.J. & Agnew, P. (1976). 'Hybrid simulation of water-turbine governors'. In R.E. Crosbie and J.L. Hay, Editors, *Simulation Councils Proceedings Series*, **6**(1). La Jolla, USA, Simulation Councils Inc., 35-44. *

Cameron, N., Thomson, D.G. & Murray-Smith, D.J. 2003 'Pilot modelling and inverse simulation for initial handling qualities assessment'. *Aeronautical Journal*, **107**, 511-520.*

Carruthers, B., McGookin, E.W. & Murray-Smith, D.J. (2005) 'Adaptive evolutionary search algorithm with obstacle avoidance for multiple UAVs'. In P.Horocek, M. Simandl and P. Zitek, Editors, *Preprints of the 16th IFAC World Congress, Prague, July 3-8, 2005*. IFAC.

Carson, E.R. & Murray-Smith, D.J. (1988), 'The conceptual basis of modelling the respiratory system'. In D.G. Cramp and E.R. Carson, Editors, *The Respiratory System*. London, UK. Croom Helm, 1-12.

Celi, R. (2000) 'Optimisation based inverse simulation of a helicopter slalom maneuver'. *Journal of Guidance, Control and Dynamics*, **23**, 289-297.

Cloud, D.J. & Rainey, L.B., Editors (1998) *Applied Modeling and Simulation*. USA. AIAA.

Conway, B.A., Lau, J.W.N., Murray-Smith, D.J. & Rosenberg, J.R. (1990) 'Techniques for the analysis of neuronal interactions'. *Journal of Physiology*, **429**, 5P.

Çimen, T. & Banks, S.P. (2004) 'Nonlinear optimal tracking control with application to super-tankers for autopilot design'. *Automatica*, **40**(11), 1845-1863.

Dasgupta, D. & McGregor, D. (1992) 'Engineering optimizations using the structured genetic algorithm'. In *Proceedings of the 1992 European Conference on Artificial Intelligence, ECAI-92*, 608-609.

Davey, N.J., Ellaway, P.H., Halliday, D.M., Murray-Smith, D.J. & Rosenberg, J.R. (1986) 'Comparative analysis of measures of association between spike trains'. *Journal of Physiology*, **377**, 14P.

Davison, E.J. (1966) 'A method for simplifying linear dynamic systems'. *IEEE Transactions on Automatic Control*, **11**, 93-101.

de Boor, C. (1978) *A Practical Guide to Splines*, Germany, Berlin. Springer Verlag.

de Matteis, G., de Socio, L.M. & Leonessa, A. (1995) 'Solution of aircraft inverse problem by local optimisation'. *Journal of Guidance, Control and Dynamics*, **18**, 567-571.

Devasia, S., Chen, D. & Paden, B. (1996) 'Nonlinear inversion-based output tracking'. *IEEE Transactions on Automatic Control*, **41**, 930-942.

Donaldson, N. de N., Gollee, H., Hunt, K.J., Jarvis, J.C. & Kwende, M.K.N. (1995) 'A radial basis function model of muscle stimulated with irregular inter-pulse intervals'. *Med. Eng. Phys.*, **17**(6), 431-441.

Dorato, P. (1969) 'On the inverse of linear dynamical systems'. *IEEE Transactions on Systems Science and Cybernetics*, **5**, 43-48.

Downie, I.C. & Murray-Smith, D.J. (1981) 'Simulation of systems involving pulse frequency modulation with special reference to modelling of muscle spindles'. In *Proceeedings 1981 UKSC Conference on Computer Simulation*. Guildford, UK, Westbury House, 143-152.

Dutia, M.B., Murray-Smith, D.J., Rosenberg, J.R. & Wilson, R. (1977) 'The dependence of "driving" of Ia axons on muscle length and fusimotor stimulation frequency'. *Journal of Physiology*, **273**, 30P-31P.

Elliott, H. & Wolovich, W.A. (1980) 'A frequency domain model reduction procedure'. *Automatica*, **16**, 67-177.

El-Shirbeeny, E.H.T, Murray-Smith, D.J. & Winning, D.J. (1974) 'A technique for direct evaluation of parameter sensitivity functions'. *Electronics Letters,* **10**(25/26), 530-531.*

Ericsen, T.S. (2005) 'Physics based design, the future of modeling and simulation'. *Acta Polytechnica*, **45**(4), 59-64.

Federov,V.V. (1972) *Theory of Optimal Experiments*. New York, USA, Academic Press.

Fossen, T.I. (1994) *Guidance and Control of Ocean Vehicles*. Chichester, UK, Wiley.

Francis, B.A.. & Wonham, W.M. (1976) 'The internal model principle of control theory'. *Automatica*, **12**, 457-465**.**

Goldberg, D. (1989) *Genetic Algorithms in Searching, Optimisation and Machine Learning.* Reading, USA, Addison-Wesley.

Gollee, H. (1998) *A Nonlinear Approach to Modelling and Control of Electrically Stimulated Skeletal Muscle*, PhD Thesis, Faculty of Engineering, University of Glasgow, Scotland, UK.

Gollee, H. & Hunt, K.J. (1997) 'Nonlinear modelling and control of electrically stimulated muscle: a local model network approach'. *International Journal of Control,* **68**(6), 1259-1288.

Gollee, H. & Murray-Smith, D.J. (1997) 'Validation of a local model network for electrically stimulated muscle'. In A.B. Bulsari and S. Kallio, Editors, *Neural Networks in Engineering Systems, Proceedings of the 1997 International Conference on Engineering Applications of Neural Networks (EANN'97).* Turku, Finland, Systems Engineering Association, 191-194.

Gollee, H., Murray-Smith, D.J. & Jarvis, J.C. (2001) 'A nonlinear approach to modeling of electrically stimulated skeletal muscle'. *IEEE Transactions on Biomedical Engineering*, **48**(4), 406-415. *

Gong, M. & Murray-Smith, D.J. (1993) 'Model reduction by an extended complex curve-fitting approach'. *Transactions of the Institute of Measurement and Control*, **15**(4), 188-198. *

Gong, M. & Murray-Smith, D.J. (1998) 'A practical exercise in simulation model validation'. *Mathematical and Computer Modelling of Dynamical Systems*, **4**(1), 100-117.

Gong, M., Oppen, I. & Murray-Smith, D.J. (1995) 'The development of tuning techniques for single-input single-output and multivariable control systems using controller sensitivity measures'. In R.C.H. Cheng and R.J. Pooley, Editors, *UKSS'95-Second Conference of the UK Simulation Society*. Edinburgh, UK, United Kingdom Simulation Society, 73-79.

Goodwin, G.C. & Payne, R.L. (1977) *Dynamic System Identification: Experiment Design and Data Analysis.* New York, USA, Academic Press.

Grant, A. & Murray-Smith, D.J. (2004) 'Polygon imaging methods in plant monitoring and model validation applications'. In *Proceedings Advanced Engineering Design 2004 Conference, Glasgow, September 2004*. Prague, Czech Republic, Orgit, Paper C1.07.

Gray, G.J., Li, Y., Murray-Smith, D.J. & Sharman, K.C. (1995) 'Specification of a control system fitness function using constraints for genetic algorithm based design methods'. In *Proceedings First IEE/IEEE International Conference on GA in Engineering Systems: Innovations and Applications, 12-14 September 1995, Sheffield, UK*. IEE Conference Publication **414**. London, UK, IEE, 530-535.

Gray, G.J., Li, Y., Murray-Smith, D.J. & Sharman, K.C. (1996a) 'Structural system identification using genetic programming and a block diagram oriented simulation tool'. *Electronics Letters*, **32**(15), 1422-1424. *

Gray, G.J., Murray-Smith, D.J., Li, Y. & Sharman, K.C. (1996b) 'Nonlinear system modelling using output error estimation of a local model network'. In *Proceedings of Society for Computer Simulation Summer Computer Simulation Conference (SCSC '96), Portland, Oregon, July 1996*. San Diego, La Jolla (Ca)., USA, Society for Computer Simulation, 460-465.

Gray, G.J., Li, Y., Murray-Smith, D.J., Ronco, E. & Sharman, K.C. (1997) 'The application of genetic algorithms to gain scheduling controller analysis and design'. In *Proceedings, Second International Conference on Genetic Algorithms in Engineering Systems: Innovations and Applications, Glasgow 2-4 September 1997*. IEE Conference Publication **446**. London, UK, IEE, 364-368.

Gray, G.J. & Murray-Smith, D.J. (1993) 'The external validation of nonlinear models for helicopter dynamics'. In R.J. Pooley and R.N. Zobel, Editors, *UKSS'93, Conference of the United Kingdom Simulation Society*. Edinburgh, UK, United Kingdom Simulation Society, 143-147.

Gray, G.J., Murray-Smith, D.J., Li, Y. & Sharman, K.C. (1997) 'Nonlinear model structure identification using genetic programming'. In I. Troch and F. Breitenecker, *Proceedings 2nd MATHMOD VIENNA IMACS Symposium on Mathematical Modelling, February 1997*. Vienna, Austria, Argesim, 301-306.

Gray, G.J., Murray-Smith, D.J., Li, Y., Sharman, K.C. & Weinbrenner, T. (1998) 'Nonlinear model structure identification using genetic programming'. *Control Engineering Practice*, **6**, 1341-1352.*

Gray, G.J, Murray-Smith, D.J., Sharman, K.C. & Li, Y. (1996) 'Nonlinear model structure identification using genetic programming'. In *Late-Breaking Papers of Genetic Programming '96 (GP '96), Stanford, California, July 1996*. 32-37.

Gray, G.J., Voon, L. K. & Murray-Smith, D.J. (1997) 'Applications of the distortion method for model validation'. In I. Troch and F. Breitenecker, Editors, *Proceedings 2nd MATHMOD VIENNA IMACS Symposium on Mathematical Modelling, February 1997*. Vienna, Austria, Argesim, 1033-1038.

Gray, G.J., Weinbrenner, T., Murray-Smith, D.J., Li, Y. & Sharman, K.C. (1997) 'Issues in nonlinear model structure identification using genetic programming'. In *Proceedings, Second International Conference on Genetic Algorithms in Engineering Systems: Innovations and Applications, Glasgow 2-4 September 1997*. IEE Conference Publication **446**. London, UK, IEE, 308-313.

Greer, W., Jordan, M.M. & Murray-Smith, D.J. (1982) 'A structural approach to respiratory control simulation'. In J.P.Paul, Editor, *Computing in Medicine*. London, UK, Macmillan, 339-346.

Gribble, J.J., Manness, M.A. & Murray-Smith, D.J. (1994) 'Helicopter flight control design: multivariable methods and design issues'. In M.V. Cook and M.J. Rycroft, Editors, *Aerospace Vehicle Dynamics and Control*. Oxford, UK, Clarendon Press, 199-224.

Gribble, J.J. & Murray-Smith, D.J. (1990) 'Command following control design by linear quadratic optimisation'. In *Proceedings 16th European Rotorcraft Forum, Glasgow, Sept. 1990*. London, UK, Royal Aeronautical Society, III.5.3.1-III.5.3.14.

Halliday,D.R., Murray-Smith, D.J. & Rosenberg, J.R. (1992) 'A frequency-domain identification approach to the study of neuromuscular systems - a combined experimental and modelling approach'. *Transactions of the Institute of Measurement and Control*, **14**(2), 79-90. *

Hamel, P. (1994) 'Aerospace vehicle modelling requirements for high bandwidth flight control'. In M.V. Cook and M.J. Rycroft, Editors, *Aerospace Vehicle Dynamics and Control*. Oxford, UK, Clarendon Press, Chapter 1.

Hasan, Z. & Houk, J.C. (1975) 'Analysis of response properties of de-efferented mammalian spindle receptors based on frequency response'. *Journal of Neurophysiology*, **38**, 663-672.

Hess, R.A., Gao, C. & Wang, S.H. (1991) 'Generalized technique for inverse simulation applied to aircraft maneuvers'. *Journal of Guidance, Control and Dynamics*, **14**, 920-926**.**

Hirschorn, R.M. (1979) 'Invertibility of multivariable nonlinear control systems'. *Journal of Guidance, Control and Dynamics*, **24**, 855-865.

Hjalmarsson, H. (2002) 'Iterative feedback tuning'. *International Journal of Adaptive Control and Signal Processing*, **16**(1), 373-395.

Hodgkin, A.I. & Huxley, A.F. (1952) 'A quantitative description of membrane current and its application to conduction and excitation in nerve'. *Journal of Physiology*, **117**, 500-544.

Holland, J.H. (1975) *Adaptation in Natural and Artificial Systems*, Cambridge, USA, MIT Press.

Hughes, G., Manness, M.A. & Murray-Smith, D.J. (1990) 'Eigenstructure assignment for handling qualities in helicopter flight control law design'. In *Proceedings 16th European Rotorcraft Forum, Glasgow, Sept. 1990*. London, UK, Royal Aeronautical Society, III.10.2.1-III.10.2.13.

Hunter, W.G., Hill, W.J. & Henson, T.L. 1969 'Designing experiments for precise estimation of some of the constants in a mechanistic model'. *Canadian Journal of Chemical Engineering*, **47**, 76-80.

Häussler, A., Li, Y., Ng, K.C., Murray-Smith, D.J. & Sharman, K.C. (1995) 'Neurocontrollers designed by a genetic algorithm'. In *Proceedings First IEE/IEEE International Conference on GA in Engineering Systems: Innovations and Applications, 12-14 September 1995, Sheffield, UK*. IEE Conference Publication **414**. London, UK, IEE, 536-542.

Ibrahim, R & Murray-Smith, D.J. (2007) 'Design, Implementation and Performance Evaluation of a fuzzy control system for a pH neutralisation process pilot plant'. In *Proceedings of International Conference on Intelligent and Advanced Systems (ICIAS 2007), Kuala Lumpur, November 2007*. Kuala Lumpur, Malaysia, Universiti Teknologi Petronas.

Isidori, A. (1995) *Nonlinear Control Systems*. 3rd Edition. London, UK. Springer.

Isidori, A. & Byrnes, C.I. (1990) 'Output regulation in nonlinear systems'. *IEEE Transactions on Automatic Control*, **35**, 3544-3548.

Jang, J-S. R. & Sun, C.-T. (1993) 'Functional equivalence between radial basis function networks and fuzzy inference systems'. *IEEE Transactions on Neural Networks*, **4**(1), 156-159.

Jarvis, J.C., Gollee, H., Kwende, M.M.N., Salmons, S. & Murray-Smith, D.J. (1996) 'Towards an optimized muscle controller'. In A. Pedotti, J. Quintern and R. Riener, Editors, *Neuroprosthetics*. Berlin, Germany, Springer, 123-128.

Jenkins, G.M. (1963) ‘Contribution to a discussion of paper by M.S. Bartlett’. *Journal Royal Statistical Society*, **B25**, 290-291.

Johansen, T.A. & Foss, B.A. (1993) ‘Constructing NARMAX models using ARMAX models’. *International Journal of Control*, **58**, 1125-1153.

Jordan, M.I. & Jacobs, R.A. (1994) ‘Hierarchical mixtures of experts and the EM algorithm’, *Neural Computation*, **6**(2), 181-214.

Kaletka,.J (1979) ‘Rotorcraft identification experience’. In *AGARD Lecture Series 104*. Paper 7.

Kavli, T. (1993) ‘ASMOD: an algorithm for adaptive spline modelling of observation data’, *International Journal of Control*, **58**(4), 947-967.

Kato, O. & Saguira, I. 1986 ‘An interpretation of airplane general motion and control as inverse problem’. *Journal of Guidance, Control and Dynamics*, **9**, 198-204.

Kirkpatrick, S., Gelatt, C.D. & Vecchi, M.P. 1983 ‘Optimization by simulated annealing’, *Science*, **220**(4598), 671-680

Kocijan, J. & Murray-Smith, D.J., (1999) ‘Robust nonlinear control for ship steering’. In N.E. Mastorakis, Editor, *Progress in Simulation, Modeling, Analysis and Synthesis of Modern Electrical and Electronic Devices and Systems*. World Scientific and Engineering Society Press, 235-240. *

Koza,J.R. 1992 *Genetic Programming: On the Programming of Computers by Means of Natural Selection*. Cambridge, MA, USA, MIT Press.

Lagarias, J.C., Reeds, J.A., Wright, M.H. & Wright, P.E. (1998) ‘Convergence properties of the Nelder-Mead simplex method in low dimensions’. *SIAM Journal of Optimization*, **9**, 112-147.

Lee, S. & Kim, Y. (1997) ‘Time domain finite element method for inverse problem of aircraft maneuvers’. *Journal of Guidance, Control and Dynamics*, **22**, 395-401.

Leith, D.J. (1994) ‘ Identification of the SA-330 Puma helicopter’. *IEE Proceedings Control Theory and Applications*, **141**(2), 130-136.

Leith, D.J., Bradley, R. & Murray-Smith, D.J. (1993) ‘Combination of data sets for system identification’. *IEE Proceedings –Part D*. **140**(1), 11-18.

Leith, D.J. & Leithead, W.E. (1998) ‘Gain-scheduled and nonlinear systems: dynamic analysis by velocity-based linearization families ’. *International Journal of Control*, **70**(2), 289-317.

Leith, D.J. & Leithead, W.E. (1999) ‘Analytical framework for blended multiple models using linear local models’. *International Journal of Control*, **72**, 605-619.

Leith, D.J. & Murray-Smith, D.J. (1989) ‘Experience with multi-step test inputs for helicopter parameter identification’. *Vertica*, **13**(3), 403-412. *

Leith, D.J. & Murray-Smith, D.J. (1993) 'The design of energy and amplitude constrained optimal inputs for system identification'. *Systems Analysis-Modelling-Simulation,* **13**(3-4), 209-238.

Levy, E.C. (1959) 'Complex curve fitting'. *IRE Transactions on Automatic Control,* **4,** 37-44.

Li, Y., Ng, K.C., Murray-Smith, D.J., Gray, G.J. & Sharman, K.C. (1996) 'Genetic algorithm automated approach to design of sliding mode control systems'. *International Journal of Control*, **63**(4), 721-739. *

Li, Y., Tan, K.C., Ng, K.C. & Murray-Smith, D.J. (1995) 'Performance based linear control system design by genetic evolution with simulated annealing'. In *Proceedings 34th IEEE Conference on Decision and Control, New Orleans, LA, 13-15 December 1995*. USA, IEEE, 731-736.

Loo, M., McGookin, E.W. & Murray-Smith, D.J. (2005) 'Sliding mode based inverse model control for oil tanker guidance'. In P.Horocek, M. Simandl and P. Zitek, Editors, *Preprints of the 16th IFAC World Congress, Prague, July 3-8, 2005*. IFAC.

Lu, L., Murray-Smith, D.J. & McGookin, E. (2006) 'Relationships between model inversion and inverse simulation techniques'. In I. Troch and F. Breitenecker, editors, *Proceedings 5th MATHMOD, Vienna, February 2006*. Vienna, Austria, Argesim/ASIM.

Lu, L., Murray-Smith, D.J. & McGookin, E.W. (2007)'Investigation of inverse simulation for design of feedforward controllers'. *Mathematical and Computer Modelling of Dynamical Systems*, **13**(5), 437-454. *

Lu, L., Murray-Smith D.J. & Thomson, D.G. (2007) 'Sensitivity-analysis method for inverse simulation application'. *AIAA Journal of Guidance, Control and Dynamics*, **30**(1), 114-121. *

Lu, L., Murray-Smith, D.J. & Thomson, D.G. (2008) 'Issues of numerical accuracy and stability in inverse simulation'. *Simulation Modelling Practice and Theory*, **16**, 1350-1364. *

Maclaine, C.G., McWilliam, P.N., Murray-Smith, D.J. & Rosenberg, J.R. (1977) 'A possible mode of action of static fusimotor axons as revealed by system identification techniques'. *Brain Research*, **135**, 351-357. *

McGookin, E.W. & Murray-Smith, D.J. (2006a) 'Submarine sliding mode controllers' optimisation using simulated annealing and genetic algorithms'. *Control Engineering Practice,* **14**(1), 1-15. *

McGookin, E.W. & Murray-Smith, D.J. (2006b) 'Comment on "Nonlinear optimal tracking control with application to supertankers for autopilot design" by T. Çimen and S.P. Banks'. *Automatica*, **42**, 2223-2225. *

McGookin, E., Murray-Smith, D.J. & Fossen, T.I. (2000) 'The use of genetic algorithms for nonlinear controller design'. *Acta Polytechnica*, **40**(3), 14-21.

McGookin, E.W., Murray-Smith, D.J. & Li, Y. (1996a) 'Segmented simulated annealing applied to sliding mode controller design'. In *Proceedings 13th World Congress of IFAC, San Francisco, USA, July 9-12, 1996*. IFAC, Volume D, 333-338.

McGookin, E.W., Murray-Smith, D.J. & Li,Y. (1996b) 'Submarine sliding mode controller optimisation using genetic algorithms. In *Proceedings UKACC International. Conference on Control, CONTROL'96, Exeter, September 1996*. London, UK, IEE, 424-429.

McGookin, E.W., Murray-Smith, D.J. & Li, Y. (1997) 'A population minimisation process for genetic algorithms and its application to controller optimisation'. In *Proceedings, Second International Conference on Genetic Algorithms in Engineering Systems: Innovations and Applications, Glasgow 2-4 September 1997*. IEE Conference Publication **446**. London, UK. IEE, 79-85.

McGookin, E.W., Murray-Smith, D.J., Li, Y. & Fossen, T.I. (1997a) 'Parameter optimisation of a non-linear tanker control system using genetic algorithms'. In *Proceedings, Second International Conference on Genetic Algorithms in Engineering Systems: Innovations and Applications, Glasgow 2-4 September 1997*. IEE Conference Publication **446**. London, UK. IEE, 37-42.

McGookin, E.W., Murray-Smith, D.J., Li, Y. & Fossen, T.I. (1997b) 'Non-linear tanker control system optimisation using genetic algorithms'. In *Proceedings Oceans'97 Conference MTS/IEEE, Halifax, Nova Scotia, Canada*, Volume 1. USA, IEEE, 17-22.

McGookin, E., Murray-Smith, D.J., Li, Y. & Fossen, T.I. (2000a) 'The optimization of a tanker autopilot control system using genetic algorithms'. *Trans. Inst. Measurement and Control*, **22**, 141-178. *

McGookin, E., Murray-Smith, D.J., Li, Y. & Fossen, T.I. (2000b) 'Ship steering control system optimisation using genetic algorithms'. *Control Engineering Practice*, **8**, 429-443. *

McLeod, J. (1966) 'PHYSBE….a physiological simulation benchmark experiment', *Simulation*, **7**(6), 324-329.

McLoone, S.C., Irwin, S.C. & McLoone, S.F. (2001) 'Constructing networks of continuous time velocity-based local models'. *IEE Proceedings, Control Theory and Applications*, **148**(5), 397-405.

Manness, M.A., Gribble, J.J. & Murray-Smith, D.J. (1990) 'Multivariable methods for helicopter flight control law design'. In *Proceedings 16th European Rotorcraft Forum, Glasgow, Sept. 1990*. London, UK, Royal Aeronautical Society, III.5.2.1-III.5.2.14.

Manness, M.A. & Murray-Smith, D.J. (1987) 'Direct assessment of parameter sensitivity in multivariable closed-loop systems'. In R.N. Zobel, Editor, *Proceedings of 1987 UKSC Conference on Computer Simulation*. Ghent, Belgium, Society for Computer Simulation, 149-153.

Manness, M.A. & Murray-Smith, D.J. (1988a) ‘A technique for the tuning of helicopter flight control systems’. In *Proceedings 14th European Rotorcraft Forum, Milan, September 1988*. 67.1-67.12.

Manness, M.A. & Murray-Smith, D.J. (1988b)‘A technique for the tuning of helicopter handling qualities’. In *Proceedings of International Conference on Helicopter Handling Qualities and Control, 15-17 November, 1988, London*. London, UK, Royal Aeronautical Society, 26.1-26.16.

Manness, M.A. & Murray-Smith, D.J. (1992) ‘Aspects of multivariable flight control law design for helicopters using eigenstructure assignment’. *Journal of the American Helicopter Society,* **37**(3),18-32.

Metropolis, N., Rosenbluth, A.W., Rosenbluth, M.N., Teller, A.H. & Teller, E. (1953) ‘Equations of state calculation by fast computing machine’, *Journal of Chemical Physics,* **21,** 1087-1092.

Mills, R.J., Middleton, S., Murray-Smith, D.J. & Pack, A.I. (1974) ‘Simulation in the teaching of concepts of respiratory gas exchange’. *International Journal of Mathematics Education in Science and Technology,* **5**, 381-387.

Mitchell, A., McGookin E.W. & Murray-Smith, D.J. (2003) ‘Comparison of control methods for autonomous underwater vehicles’. In *Proceedings of the 1st IFAC Workshop on Guidance and Control of Underwater Vehicles (GCUV2003), Newport, Wales*. IFAC, 41-46.

Mitchell, A.J., McGookin, E.W. & Murray-Smith, D.J. (2005) ‘Implementation of sliding mode observer based reconfiguration in an autonomous underwater vehicle’, *Acta Polytechnica,* **45**(4), 18-24.

Murray-Smith, D.J. (1982) ‘System identification and parameter estimation techniques in the modelling of physiological systems - a review’. In J.P.Paul, Editor, *Computing in Medicine*. London, UK, Macmillan, 333-338.

Murray-Smith, D.J. (1983) ‘Use of an aircraft lateral beam guidance system simulation in the teaching of control engineering’. In W. Ameling, Editor, *Proceedings of 1st European Simulation Congress ESC83*. Informatik-Fachberichte, No. 71. Berlin, Germany, Springer, 337-342.

Murray-Smith, D.J. (1984) ‘Use of a hydro-electric generation system simulation in the teaching of control engineering’. In D.J. Murray-Smith, Editor, *Proceedings of the 1984 UKSC Conference on Computer Simulation, 12-14 September 1984,University of Bath*. London, UK, Butterworth, 451-457.

Murray-Smith, D.J. (1986) ‘Investigations of methods for the direct assessment of parameter sensitivity in linear closed loop control systems’. In S.G. Tzafestas and P. Borne, Editors, *Complex and Distributed Systems: Analysis, Simulation and Control*. Amsterdam, The Netherlands, North Holland, 323-328. *

Murray-Smith, D.J. (1990a) ‘A review of respiratory system applications of computer simulation and modelling techniques’. In D. Möller, Editor, *Advanced Simulation in Biomedicine*. New York, USA, Springer, 83-116.

Murray-Smith, D.J. (1990b) ‘A review of methods for the validation of continuous system simulation models’. In K.G. Nock, Editor, *Proceedings 1990 UKSC Conference on Computer Simulation*. Burgess Hill, UK, United Kingdom Simulation Council, 108-111.

Murray-Smith, D.J. (1991a) ‘Identification methodologies: Flight test procedures’. In *AGARD Advisory Report 280: Rotorcraft System Identification (AGARD-AR-280)*. Neuilly sur Seine, France, AGARD, 51-57.

Murray-Smith, D.J. (1991b) ‘Robustness issues’. In *AGARD Advisory Report 280: Rotorcraft System Identification (AGARD-AR-280)*. Neuilly sur Seine, France, AGARD, 213-222.

Murray-Smith, D.J. (1991c) ‘Modelling aspects and robustness issues in rotorcraft system identification’. In *AGARD Lecture Series 178: Rotorcraft System Identification (AGARD-LS-178)*. Neuilly sur Seine, France, AGARD, 7.1-7.9.

Murray-Smith, D.J. (1992) ‘Problems and prospects in the validation of dynamic models’. In A. Sydow, Editor, *Computational Systems Analysis 1992, Proceedings 4th International Symposium on Systems Analysis and Simulation, Berlin, Germany*. Amsterdam, The Netherlands, Elsevier, 21-27.

Murray-Smith, D.J. (1994) ‘The development, validation and application of a simulation model of active skeletal muscle’. In J. Halin, W. Karplus and R. Rimane, Editors, *Proceedings CISS - First Joint Conference of International Simulation Societies, August 22-25 1994, Zürich, Switzerland*. La Jolla, USA, Society for Computer Simulation, 600-604.

Murray-Smith, D.J. (1995a) ‘Modelling limitations for helicopter flight control system design’. In F. Breitenecker and I. Husinsky, I., Editors, *EUROSIM'95 Simulation Congress*. Amsterdam, The Netherlands, Elsevier, 397-402. *

Murray-Smith, D.J. (1995b) ‘Advances in simulation model validation: theory, software and applications’. In F. Breitenecker, and I. Husinsky, Editors, *Proceedings EUROSIM'95 Simulation Congress*. Amsterdam, The Netherlands, Elsevier, 75-84.

Murray-Smith, D.J. (1998) ‘Methods for the external validation of continuous system simulation models’. *Mathematical and Computer Modelling of Dynamical Systems*, **4**(1), 5-31.

Murray-Smith, D.J. (2000a) ‘Issues of model accuracy and external validation for control system design’. *Acta Polytechnica*, **40**(3,) 8-13.

Murray-Smith, D.J. (2000b) “The inverse simulation approach: a focused review of methods and applications”. *Mathematics and Computers in Simulation*, **53**, 239-247.

Murray-Smith, D.J. (2002) “The validation of computer-based models in engineering: some lessons from computing science”. *Acta Polytechnica*, **41**(4-5), 45-48.

Murray-Smith, D.J. (2003a) “A case-study based approach to modelling and simulation education”. In I. Troch and F. Breitenecker, Editors, *Proceedings 4th MATHMOD, Vienna, February 2003*. Vienna, Austria, Argesim, 295-302.

Murray-Smith, D.J. (2003b) “Biological systems thinking for control engineering design”. In *Proceedings Advanced Engineering Design 2003 Conference, Prague, June 2003*. Prague, Czech Republic, Orgit, Paper F5.5.

Murray-Smith, D.J. (2003c) “An approach to closed-loop system design and sensitivity analysis based on s-plane geometry”. In I. Troch and F.Breitenecker, Editors, *Proceedings of 4th MATHMOD Symposium, Vienna, February 2003*. Vienna, Austria. Argesim, 1456-1465.

Murray-Smith, D.J. (2004a) ‘Issues of model quality and inverse simulation in introducing students to concepts of integrated control system design’. In *Proceedings Advanced Engineering Design 2004 Conference, Glasgow, September 2004*. Prague, Czech Republic, Orgit, Paper E1.09.

Murray-Smith, D.J. (2004b) ‘Software for closed-loop system design and sensitivity analysis based on s-plane geometry and its use in the teaching of control engineering design principles’. In *Proceedings Advanced Engineering Design 2004 Conference, Glasgow, September 2004*. Prague, Czech Republic, Orgit, 2004, Paper E1.07.

Murray-Smith, D.J. (2005) ‘Biomimetic and human supervisory concepts for intelligent control’. In *Proceedings of International Conference on Intelligent Systems (ICIS2005), 1-3 December 2005, Kuala Lumpur, Malaysia.*. Universiti Teknologi Petronas, Plenary Lecture No. 1.

Murray-Smith, D.J. (2006a) ‘Simulation model quality issues in engineering: a review’. In I. Troch and F. Breitenecker, Editors, *Proceedings 5th MATHMOD, Vienna, February 2006*. Vienna, Austria, Argesim/ASIM. *

Murray-Smith, D.J. (2006b) ‘Neuromuscular Systems’. In M. Akay, Editor, *Wiley Encyclopedia of Biomedical Engineering*. Hoboken, N.J., USA, Wiley, 2006, Paper 0839.

Murray-Smith, D.J., Bradley, R. & Leith, D.J. (1993) ‘Identifiability analysis and experimental design for simulation model validation’. In F. Maceri and G. Iazeolla, Editors, *EUROSIM’92 Simulation Congress*. Amsterdam, The Netherlands, North Holland, 15-20.

Murray-Smith, D.J. & Carson, E.R. (1988a) ‘The modelling process in respiratory medicine’. In D.G. Cramp and E.R. Carson, Editors, *The Respiratory System*. London, UK, Croom Helm, 296-333.

Murray-Smith, D.J. & Carson, E.R. (1988b) ‘Case studies of respiratory system models’. In D.G. Cramp and E.R. Carson, Editors, *The Respiratory System*. London, UK, Croom Helm, 334-389.

Murray-Smith, D.J., Kocijan, J. & Gong, M. (2003) 'A signal convolution method for estimation of controller parameter sensitivity functions for tuning of feedback control systems by an iterative process'. *Control Engineering Practice*, **11**(9), 1087-1094. *

Murray-Smith, D.J. & Lu, L. (2008) 'Inverse simulation methods and applications'. In *Proceedings of Grand Challenges in Modeling and Simulation Conference, Edinburgh, June 2008*, (one strand of *Summer Computer Simulation Multi-Conference*). La Jolla, CA, USA, Society for Computer Simulation, 143-150. *

Murray-Smith, D.J., Lu, L. & McGookin, E.W. (2008). "Application of inverse simulation methods to a nonlinear model of an underwater vehicle". In *Proceedings of Grand Challenges in Modeling and Simulation Conference, Edinburgh, June 2008*, (one strand of *Summer Computer Simulation Multi-Conference*), La Jolla, CA, USA, Society for Computer Simulation, 135-141.*

Murray-Smith, D.J., Murray-Smith, E, Rosenburg, J.R. & Junge, D (1995) 'GAPTUTOR – A simulation-based tutorial introduction to methods of analysis of neuronal interactions'. In F. Breitenecker and I. Husinsky (Editors), *Proceedings EUROSIM'95*. Amsterdam, The Netherlands, Elsevier Science, 1329-1334.

Murray-Smith, D. & Pack, A. (1977) 'Techniques of computer simulation applied to respiratory gas exchange'. In D.E.M. Taylor and J.S. Whamond, Editors, *Non Invasive Clinical Measurement*. London, UK, Pitman Medical, 186-202.

Murray-Smith, D.J. & Padfield, G.D. (1991) 'Design of Experiments'. In *AGARD Lecture Series 178: Rotorcraft System Identification (AGARD-LS-178)*. Neuilly sur Seine, France, AGARD, 2.1-2.8.

Murray-Smith, D.J. & Rosenberg, J.R. (1983) 'Models of the muscle spindle: a case study in physiological system simulation'. In W. Ameling, Editor, *Proceedings of 1st European Simulation Congress ESC83*. Informatik-Fachberichte No. 71. Berlin, Germany, Springer, 519-523.

Murray-Smith, D.J., Rosenberg, J.R. & Rigas, A. (1987) 'Muscle spindle modelling and identification'. In M. Singh, Editor, *Systems and Control Encyclopedia*. Oxford, UK, Pergamon, 3238-3242.

Murray-Smith, D.J., Rosenberg, J.R., Halliday, D. & Rigas, A. (1985) 'The identification of a complex biological receptor'. In H.A. Barker, and P.C. Young, Editors, *Proceedings of the 7th IFAC/IFORS Symposium on Identification and System Parameter Estimation, York, 1985*. Oxford, UK, Pergamon, **5**, 1595-1602. *

Murray-Smith, D.J. & Wong, B.O. (1997) 'Inverse simulation techniques applied to the external validation of nonlinear dynamic models'. In P. Luker, Editor, *UKSim'97, Third Conference of the United Kingdom Simulation Society, Keswick, April 1997*. Edinburgh, UK, UKSim, 100-104.

Murray-Smith, D.J. & Zhao, S. (2007) 'A graduate-level multi-purpose educational case study on modelling and simulation of the neuromuscular system'. In B.Zupančič, R.Karba and S. Blažič, Editors, *Proceedings EUROSIM 2007, 9-13 September 2007, Ljubljana, Slovenia*. Ljubljana, Slovenia. SLOSIM. 2007.

Murray-Smith, R. (1994) *A Local Model Network Approach to Nonlinear Modelling.* PhD Thesis, University of Strathclyde, Glasgow, UK.

Murray-Smith, R. & Johansen, T.A. (1997), Editors, *Multiple Model Approaches to Modeling and Control.* London, UK, Taylor and Francis.

Nelder, J.A. & Mead, R. (1965) 'A simplex method for function minimization'. *Computer Journal*, **7**, 308-313.

Nelles, O. (2001) *Nonlinear System Identification*. Berlin, Germany. Springer.

Ng, K.C., Li, Y., Murray-Smith, D.J. & Sharman, K.C. (1995) 'Genetic algorithms applied to fuzzy sliding mode controller design'. In *Proceedings First IEE/IEEE International Conference on GA in Engineering Systems: Innovations and Applications, 12-14 September 1995, Sheffield, UK*. IEE Conference Publication No. 414. London, UK, IEE, 536-542.

Olsen, O.H. & Murray-Smith, D.J. (1993) 'Quantifying periodic activity in central pattern generators: the crayfish swimmeret'. *Journal of Neuroscience Methods*, **50**, 25-35.

O'Reilly, J. & Leithead, W.E. (1991) 'Multivariable control by "Individual Channel Design"'. *International Journal of Control*, **54**(1), 1-46 (7).

Ostroversnik, M. & Murray-Smith, D.J. (1995) 'OOSlim – An experimental object oriented continuous simulation language'. In *Proceedings ERK'95, Portoroz, Slovenia, September 1995*. **A** , 285-288.

Ostroversnik, M & Murray-Smith, D.J. (1996) 'OOSlim'. In *Proceedings of 1996 European Simulation Symposium (ESS 96), October 1996, Genoa, Italy.* Ghent, Belgium.

Ostroversnik, M. & Murray-Smith, D.J. (1998) 'Real modularity in dynamic system simulation languages'. *Systems Analysis-Modelling-Simulation*, **31**(3), 69-182. *

Ostroversnik, M., Murray-Smith, D.J., Zupančič, B. & Strmčnik, S. (2000) 'OO PHYSBE model – a benchmark for modular object-oriented dynamic system simulation tools'. In *Proceedings 3rd MATHMOD, Vienna, February 2-4, 2000*. Vienna, Austria. Argesim/ASIM, **2**, 595-598. *

Pack, A.I., Emery, B., Moran, F. & Murray-Smith, D.J. (1974) 'Computer models of gas exchange processes in pulmonary ventilation'. In B. Wyke, Editor, *Ventilatory and Phonatory Control Systems*. Oxford, UK, Oxford University Press, 227-247.

Pack, A.I. & Murray-Smith, D.J. (1972) 'Mathematical models and their applications in medicine'. *Scottish Medical Journal*, **17**, 401-409.

Padfield, G.D. & Murray-Smith, D.J. (1991) 'Identification results:- Case Study iii: Sa-330 Puma'. In *AGARD Advisory Report 280: Rotorcraft System Identification (AGARD-AR-280)*. Neuilly sur Seine, France. AGARD, 176-212.

Padfield, G.D., Thorne, R., Murray-Smith, D.J., Black, C. & Caldwell, A.E. (1987) 'U.K. research into system identification for helicopter flight mechanics'. *Vertica*, **11**(4), 665-684.

Parry, D.L.K. & Murray-Smith, D.J. (1985) 'The application of modal control to the single rotor helicopter'. In *Proceedings of 11th European Rotorcraft Forum, London, September 1985*. London, Royal Aeronautical Society, 78.1-78.18.

Paterson, C.S. & Murray-Smith, D.J. (1987) 'Observers for state estimation and fault detection – a simulation study'. In R.N. Zobel, Editor, *Proceedings of 1987 UKSC Conference on Computer Simulation*. Ghent, Belgium. Society for Computer Simulation, 174-180.

Payne, P.A. (1970) 'An improved technique for transfer function synthesis from frequency response data', *IEEE Transactions on Automatic Control*, **14**, 480-483.

Pfeiffer, B.-M. & Isermann, R. (1994) 'Criteria for successful applications of fuzzy control'. *Engineering Applications of Artificial Intelligence*, **7**(3), 245-253.

Plaetschke, E. & Shulz, G, (1979) 'Practical input signal design'. In *AGARD Lecture Series 104.* Neuilly sur Seine, France, AGARD, paper 3.

Poppele, R.E. & Bowman, R.J. (1970) 'Quantitative description of linear behaviour of mammalian muscle spindles'. *Journal of Neurophysiology* , **33**, 59-72.

Press, W.H., Flannery, B.P., Teukolsky, S.A. & Vetterling, W.J. (1986) *Numerical Recipes*. Cambridge, UK, Cambridge University Press.

Priestly, M.B. (1963) 'Contribution to a discussion of paper by M.S. Bartlett'. *Journal Royal Statistical Society*, **B25**, 288-290.

Prochazka, A. (1996) 'The fuzzy logic of visuomotor control', *Canadian Journal of Physiology and Pharmacology*, **74**, 456-462.

Prochazka, A., Gillard, D. & Bennet, D.J. (1997) 'Implications of positive feedback in the control of movement', *Journal of Neurophysiology*, **77**, 3237-3251.

Prochazka, A., Gritsenko, V. & Yakovenko, S. (2002) 'Sensory control of locomotion: reflexes versus higher-level control'. In S.G. Gandevia, U. Proske & D.G. Stuart, Editors, *Sensorimotor Control*, New York, USA. Kluwer Academic/Plenum.

Raol, J.R., Girija, G. & Singh, J. (2004) *Modelling and Parameter Estimation of Dynamic Systems*. IET Control Engineering Series No. 65. UK, IEE.

Rosenberg, J.R., Murray-Smith, D.J. & Rigas, A. (1982) 'An introduction to the application of system identification techniques to elements of the neuromuscular system'. *Transactions of the Institute of Measurement and Control*, **4**(2), 187-201. *

Rudjord,T. (1972) 'Model study of muscle spindle primary endings subjected to dynamic fusimotor activation'. *Kybernetik*, **11**, 148-153.

Rumsfeld, D.H. (2002, February 12) DoD News Transcript Secretary Rumsfeld and Gen. Myers, U.S. Department of Defense, Office of the Assistant Secretary of Defense (Public Affairs). [Online] URL: http://www.defenselink.mil/transcripts/transcript.aspx?transcriptid=2636 [Accessed 9th May 2009].

Rutherford, S. & Thomson, D.G. (1996) 'Improved methodology for inverse simulation'. *Aeronautical Journal*, **100**, 79-86.

Sanathanan, C.K. & Koerner, J. (1963) 'Transfer function synthesis as a ratio of two complex polynomials', *IEEE Transactions on Automatic Control*, **8**, 56-58.

Sayers. M.W. & Han, D. (1995) 'A generic multibody vehicle for simulating handling and braking'. In *Proceedings 1995 Symposium of International Association of Vehicle System Designers, Ann Arbor, USA.*

Shorten, R., Murray-Smith, R., Bjørgan, R. & Gollee, H. (1999) 'On the interpretation of local models in blended model structures'. *International Journal of Control*, **72**(7/8), 620-628.

Silvey, S.D. (1975) *Statistical Inference*. London, UK. Chapman & Hall.

Simensen, R. & Murray-Smith, D.J. (1995) 'Ship steering control by neural networks trained using feedback linearization control laws'. In J. Kocijan and R. Karba, Editors, *Preprints IFAC/IMACS International Workshop on Artificial Intelligence in Real-Time Control, Bled, Slovenia, Nov. 29-Dec. 1, 1995.* IFAC. *

Skogestad, S. & Postlethwaite, I. (1996) *Multivariable Feedback Control: Analysis and Design*. Chichester, UK, Wiley.

Slotine, J.E. & Li, W. (1991) *Applied Nonlinear Control*. Englewood Cliffs, NJ, USA, Prentice Hall.

Smith, M.I., Murray-Smith, D.J. & Hickman, D. (2007a) 'Mathematical and computer modeling of electro-optic systems using a generic modelling approach'. *Journal of Defense Modeling and Simulation* 2007, **4**(1), 3-16. *

Smith, M.I., Murray-Smith, D.J. & Hickman, D. (2007b) 'Verification and validation issues in a generic model of electro-optic sensor systems'. *Journal of Defense Modeling and Simulation*, **4**(1), 17-27. *

Solak, E., Murray-Smith, R., Leithead, W.E., Leith, D.J. & Rasmussen, C.E. (2003) 'Derivative observations in Gaussian Process models of dynamic systems'. In *Advances in Neural Information Processing 16, Vancouver, Canada*. Cambridge, Mass., USA. MIT Press.

Söderström, T & Stoica, P. (1989) *System Identification*. New York, USA, Prentice-Hall.

Takagi, T. & Sugeno, M. (1985) 'Fuzzy identification of systems and its application to modeling and control'. *IEEE Transaction on System Man and Cybernetics*, **15(1)**, 116-132.

Tan, K.C., Li, Y., Murray-Smith D.J. & Sharman, K.C. (1995) 'System identification and linearisation using genetic algorithms with simulated annealing'. In *Proceedings First IEE/IEEE International Conference on GA in Engineering Systems: Innovations and Applications, 12-14 September 1995, Sheffield, UK*. IEE Conference Publication No. 414. London, UK, IEE, 164-169.

Thamrin, H. & Murray-Smith D.J. (2007) 'Modelling of the respiratory system for exercise conditions: a case study in physiological system simulation'. In B. Zupančič, R. Karba and S. Blažič, Editors, *Proc. EUROSIM 2007, 9-13 September 2007, Ljubljana, Slovenia*. Ljubljana, Slovenia, SLOSIM.

Thomson, D.G. & Bradley, R. (1990) "The use of inverse simulation for conceptual design". In *Proceedings of 16th European Rotorcraft Forum, Glasgow, U.K. 16-18 September 1990*. London, UK, Royal Aeronautical Society.

Thomson, D.G. & Bradley, R. (1994) "The contribution of inverse simulation to the assessment of helicopter handling qualities". In *Proceedings of the 19th ICAS Conference, Anaheim, USA, September 1994*, 229-238.

Thomson, D.G. & Bradley, R. (1998) "The principles and practical application of helicopter inverse simulation". *Simulation Practice and Theory*, **6**, 47-60.

Thomson, D.G. & Bradley, R. (2006) "Inverse simulation as a tool for flight dynamics research – principles and applications". *Progress in Aerospace Sciences*, **42**, 174-210.

Tischler, M.B. (1987) *Frequency –response Identification of the XV-15 Tilt-rotor Aircraft Dynamics*, PhD Thesis, Stanford University, CA, USA.

Tischer, M.B. (Editor) (1996) *Advances in Aircraft Flight Control*. London, Taylor & Francis.

Tischler, M.B. & Remple, R.K. (2006) *Aircraft and Rotorcraft System Identification*. USA. AIAA.

t'Mannetje, J.J. (1973) 'Transfer function identification using a complex curve-fitting technique'. *Journal of Mecahnical Engineering Science*, **15**(5), 339-345.

Tomović , R. (1963) *Sensitivity Analysis of Dynamic Systems*. New York, USA, McGraw-Hill.

Unar, M.A. & Murray-Smith, D.J. (1997) 'Radial basis function networks for ship steering control'. In *Proceedings 12th International Conference on Systems Engineering, ICSE'97, Coventry University, U.K., 9-11 September 1997*. 700-705.

Unar, M.A. & Murray-Smith, D.J. (1999) 'Automatic steering of ships using neural networks'. *International Journal of Adaptive Control and Signal Processing*, **13**, 203-218. *

van Berlekom, W.B. & Goddard, T.A. (1972) 'Maneuvering of large tankers', *Transactions of SNAME*, **80**, 264-298.

van Laarhoven, P.J.M. & Aarts, E.H.L. (1987) *Simulated Annealing: Theory and Applications*. Dordrecht, Lancaster.

Visser, W.P.J. & Broomhead, M.J. (2000) *GSP: A generic object-oriented gas turbine simulation environment*. Flight Division Technical Report NLR-Tp-2000-267. Amsterdam, The Netherlands, National Aerospace Laboratory (NLR).

Winning, D.J., El-Shirbeeny, E.H.T., Thompson, E.C. & Murray-Smith, D.J. (1977) 'Sensitivity method for online optimisation of a synchronous generator excitation controller', *Proceedings IEE, Part D – Control Theory and Applications*, **124**, 631-638.

Zenor, J.J., Murray-Smith, D.J., McGookin, E.W. & Crosbie, R.E. (2009) 'Development of a multi-rate simulation model of an unmanned underwater vehicle for real-time applications'. In I. Troch and F. Breitenecker, Editors, *Proceedings MATHMOD 09, Vienna, February 9-13, 2009*. Vienna, Austria, Argesim/Asim, 1951-1957.

Zou, Q. & Devasia, S. 2004 'Preview-based inversion of nonlinear nonminimum-phase systems: VTOL example'. In *Proceedings of the 43rd IEEE Conference on Decision and Control, Bahamas, 14-17 December, 2004*. IEEE, 4350-4356.