Preface

0.0.1 Dedication: Peter Young (1939-), engineer, academic and polymath

This book is dedicated to Professor Peter Young's 70th birthday. The majority of the authors in this book are Peter Young's friends, collaborators, former colleagues, and former students.

Professor Peter Young is a major pioneer in the development of recursive estimation and its use in adaptive forecasting, data assimilation and adaptive control system design. He has over 40 years experience in academic and industrial research, with more than 250 publications in the open literature including several books. He has made important research contributions to the areas of time series analysis, environmental modelling and computer-aided control system design. He is the leading expert on the identification and estimation of data-based transfer function models and has successfully promoted their use in forecasting and control system design.

It is through a strong contextual focus on applications in diverse fields that Peter has made such innovative contributions to generic methods, algorithms and their associated software. His environmental applications experience includes: water quality modelling and control; and rainfall-flow modelling and its use in adaptive forecasting, flood warning and data assimilation. In the earth sciences he has contributed to: weather radar calibration; climate modelling and data analysis. Other contributions include climate control in agricultural buildings; and the modelling and control of inter-urban traffic systems.

Peter is an archetypal example of the ever-inquiring charismatic researcher, always passionately challenging themselves and colleagues with new questions and ideas. His resultant collaborations have been with co-workers in many research institutions across the globe. This book dedicated to Peter is a testament to, and celebration of, the depth and breadth of his influences.

0.0.2 Theory of System Identification

Peter Young became interested in data-based modelling of dynamic systems when he was a student apprentice in the UK aircraft industry (English Electric Aviation, now BAe Systems). In 1961, he realised the limitations of least squares linear regression analysis when there was noise on the regressors and this led him to look at various approaches to this problem, particularly in relation to the estimation of parameters in dynamic systems. Because of its simplicity, he was attracted to the, at that time, little known *Instrumental Variable* (IV) method. The rest is, as they say, history. Peter started serious research on IV methods, first at Loughborough University of Technology in 1963, then in the Engineering Department of Cambridge University in 1965. During this time, he realised the importance of prefiltering data when estimating parameters in *Transfer Function* (TF) models, both to avoid the direct differentiation of noisy data, in the case of continuous-time TF models, and to improve the statistical efficiency of the estimates in both continuous and discrete-time TF models. Finally, after moving to take up a Research Chair at the Australian National University in 1975, he put all of his previous results together [1], and showed that, under the usual statistical assumptions (noise-free input variables and a rational spectral density noise process described by an ARMA process), his iterative or recursive-iterative *Refined Instrumental Variable* (RIV) estimation procedure, involving appropriate adaptively updated prefilters, was asymptotically equivalent to statistically efficient maximum likelihood estimation and prediction error minimization. Moreover, both then and now, it is unique in its ability to estimate parameters in both discrete *and* continuous-time TF models from sampled data. This RIV approach was implemented and thoroughly evaluated later by Peter and Professor Tony Jakeman, who was Peter's research colaborator at the time [2]. And recent papers [3, 4] have extended these results to include an improved IV method of ARMA noise model estimation and a three stage RIV procedure for estimating a TF model in a closed loop control system.

Given this abiding interest in the concept of instrumental variable estimation and its implementation in parameter estimation algorithms of various types, it is appropriate in this Festschrift for Peter that the first two chapters deal with aspects of this topic. The book begins with a tutorial-style chapter on instrumental variables by Professor Torsten Söderström, who has also had a life-long interest in IV estimation. A general derivation of the covariance matrix of the IV parameter estimates is presented and it is shown how this matrix is influenced by a number of user choices regarding the nature of the instrumental variables and the estimation algorithm. The chapter discusses how these user choices can be made in order to ensure that the covariance matrix is as small as possible, in a well-defined sense, and compares optimal instrumental variable algorithms with the alternative prediction error method. In particular, it discusses optimal instrumental variable methods that yield statistically efficient parameter estimates and shows that the iterative Refined RIV algorithm (referred to in the chapter as as a'multistep' algorithm) proposed by Peter in the context of the maximum likelihood estimation of Box-Jenkins transfer function models, possesses these optimal properties.

The original papers on the implementation of the RIV method by Peter Young and Tony Jakeman included results that demonstrated how the Simplified RIV (SRIV) method could be used for estimating the parameters in a hybrid continuous-time transfer function model (i.e. a continuous time system model with an additive, discrete-time noise model) from sampled data. In recent years, Peter has worked closely with Professor Hugues Garnier and Dr. Marion Gilson on the development of the full RIV version of this hybrid algorithm. In Chapter 2, Marion and Hugues, together with their colleague Vincent Laurain, investigate instrumental variables in the context of nonlinear system identification. In particular, they present RIV estimation methods for discrete or hybrid continuous-time Hammerstein models with coloured additive noise described by a discrete-time ARMA process. In order to use a regression form of solution and avoid gradient optimization, the Hammerstein model is reformulated as a linear, augmented multi-input-single-output model. The performance of the proposed methods are demonstrated by relevant Monte Carlo simulation examples.

Identifiability is a very important aspect of model identification and parameter estimation. In a useful, tutorial-style Chapter 3, Professor Eric Walter investigates identifiability with the aim of helping readers decide whether identifiability and the closely connected property of distinguishability are theoretically important and practically relevant for their research or teaching. The chapter discusses methods that can be used to test models for these properties and shows that measures of identifiability can be maximized, provided that there are some degrees of freedom in the procedure for data collection that allow for optimal experimental design. Finally, the paper shows that interval analysis and bounded parameter estimation can provide useful procedures when the model of interest cannot be made identifiable. Consistent with the tutorial nature of the chapter, simple illustrative examples are included and worked out in detail.

Professor Bruce Beck was one of Peter Young's first research students in the Control and Systems Division of the Engineering Department at Cambridge University, UK, and both of their careers were profoundly affected by the joint work they did together at this time. Although their subsequent research has moved in somewhat different directions, they have both pursued an underlying inductive approach to the identification of model structure from real experimental or monitored data, mostly in relation to environmental applications. In Chapter 4, Bruce, together with his colleagues Z Lin, and Hans Stigter, continue with this theme and address the important issues involved in model structure identification and the growth of knowledge, including novel recent research into the possibility of diverting the software of molecular graphics into serving the purpose of scientific visualization in supporting the procedural steps of model structure identification.

Inspired by the work of Peter Young, who has made a life time of contributions to parameter estimation for real world systems, several chapters follow on the general identification concepts and technology. Professor Graham Goodwin is one of the most important contributors to the theory and practice of automatic control over the past forty years and is a long-time and valued friend of Peter Young. In Chapter 5, Graham combines with Mauricio Cea to consider the problem of joint state and parameter estimation for continuous time systems in the important practical situation where data are collected with non-uniform sampling intervals. This problem is formulated in the context of nonlinear filtering and the chapter shows how a new class of nonlinear filtering algorithm *Minimum Distortion Filtering* (MDF) can be applied to this problem. A simple example is used to illustrate the performance of the algorithm and the results are compared with those obtained using numerically intensive *Particle Filtering*. It is clear that, in this example, the MDF approach has distinct advantages in both computational and estimation terms.

In the nineteen seventies, Victor Solo was a research student at the Australian National University supervised by the noted expert on time series analysis, Professor Ted Hannan, and Peter Young. Since then Victor has worked at the cutting edge of research on novel aspects of both the theory and practice of time series analysis. In Chapter 6, Victor first notes that adaptive signal processing and adaptive control developed slowly and independently until the 1970s. And he points out that Peter Young was one of the pioneers in this area of study and that Peter's 1984 book *Recursive Estimation and Time Series Analysis* (a heavily revised and expanded version of which will appear soon) is one of the few books of this era that discusses the use of fixed gain recursive algorithms for *Time Varying Parameter* (TVP) estimation, as well as TVP estimation in an off-line setting, exploiting recursive smoothing. In the former context, Victor's main aim is to discuss the powerful tool of 'averaging analysis' that can be used to evaluate the stability of recursive estimation algorithms. He points out that, although adaptive or learning algorithms have found wide use in control, signal processing and machine learning, the use of averaging analysis is not as well known as it should be. He reviews this approach within the context of the adaptive *Least Mean Square* (LMS) type of algorithm and develops averaging in a heuristic manner, illustrating its use on a number of illustrative examples.

In Chapter 7, Professor Manfred Deistler, another old friend of Peter Young's and one of the most important time series analysts of his day, combines with his colleagues Christoph Flamm, Ulrike Kalliauer, Markus Waser and Andreas Graef, to describe measures for dependence and causality between component processes in multivariate time series in a stationary context. Symmetric measures, such as the partial spectral coherence, as well as directed measures, such as the partial directed coherence and the conditional Granger causality index, are described and discussed. These measures are used for deriving undirected and directed graphs (where the vertices correspond to the one-dimensional component processes), showing the inner structure of a multivariate time series. The authors' interest in these graphs originates from the problem of detecting the focus of an epileptic seizure, based on the analysis of invasive EEG data and an example for such an analysis is given in the last section of the chapter.

Although they are not in the same Department at Lancaster, Professor Granville Tunnicliffe-Wilson and Peter Young have been friends and colleagues for many years. Together, they helped Peter Armitage, from the Civil Service College in London, with courses on forecasting for Civil Servants that were held in London and Lancaster. It is notable that Granville was a research student of Professor Gwilym Jenkins at Lancaster and contributed much to the writing of the famous 1970 book by Jenkins and George Box on time series analysis, forecasting and control. It is appropriate, therefore, that Chapter 8, by Granville and Peter Armitage, is a tutorial-style chapter on Box-Jenkins methods; methods that are now used across the world, not least because they have been incorporated into standard software, such as the X11-ARIMA seasonal adjustment package developed by the US Bureau of the Census. The exposition is not, however, limited to the Box and Jenkins approach and other methods of model structure identification are suggested. The chapter is based on a series of times series case studies, ranging from the airline series example presented by Box and Jenkins, to an example of half hourly electricity demand. This chapter also serves as a fitting memorial to Peter Armitage, who died recently but who did so much to further the adoption of advanced forecasting methods in the UK Civil Service.

State Dependent Parameter (SDP) modelling was developed by Peter Young in the 90's to identify non-linearities in the context of dynamic transfer function models [5]. SDP estimation is based on exploiting the recursive Kalman Filter (KF) and Fixed Interval Smoothing (FIS) algorithms to produce non-parametric estimates (graphs) of the model parameters as a function of other measured variables. This approach, which is very useful for locating the position and form of the nonlinearities prior to their parameterization, has been applied successfully in many application areas, especially to identify the structure of nonlinear Data-Based Mechanistic (DBM) models (see chapter 16) from observed time series data. In Chapter 9, Drs. Marco Ratto and Andrea Pagano, highlight other applications of SDP modelling, where fruitful co-operation with Peter has led to a series of joint papers in which *State-Dependent Regression* (SDR) analysis has been applied to perform various useful functions in sensitivity analysis, dynamic model reduction and emulation ('meta') modelling, where a linked set of reduced order models is capable of reproducing closely the main static and dynamic features of large computer simulation models (see also chapters 10 and 16). The chapter also describes how SDR algorithms can be used to identify and improve the performance of tensor product smoothing spline ANOVA models.

SDP modelling is also considered in Chapter 10, which is contributed by Peter Young's colleagues from Lancaster, Drs. Wlodek Tych, Paul Smith, Arun Chotai and James Taylor, together with a former research student, Jafar Sadeghi. This describes and develops Jafar and Wlodek's generalization of the SDP approach to include *Multi-State Dependent Parameter* (MSDP) nonlinearities. The recursive estimation of the MSDP model parameters in a multivariable state space occurs along a multi-path trajectory, again employing the KF and FIS algorithms. The novelty of the method lies in redefining the concepts of sequence (predecessor, successor), so allowing for their use in a multi-state dependent context and facilitating the subsequent efficient parameterisation for a fairly wide class of non-linear, stochastic dynamic systems. The approach is illustrated by two worked examples in MATLAB. The format of the estimated SDP model also allows its direct use in new methods of SDP control system design within a *Non-Minimal State Space* (NMSS) control system design framework, as originally suggested by Peter Young (see Chapter 27).

Peter Young has been friends with Professor Liuping Wang for the last decade and, over the last few years, he has worked with her on both a NMSS-based formulation of model predictive control and SDP model estimation using wavelets. In Chapter 11, Liuping and her colleague Nguyen-Vu Truong continue with the SDP theme and apply a new SDP-based approach to the important problem of electrical demand forecasting. Such forecasting is critical to power system operation, since it serves as an input to the management and planning of activities such as power production, transmission and distribution, the dispatch and pricing process, as well as system security analysis. From the system's point of view, this is a *complex nonlinear dynamic system* in which the power demand is a highly nonlinear function of the historical data and various external variables. The chapter describes an application of an SDP model based on a two-dimensional wavelet (2-DWSDP) to the forecasting of daily peak electrical demand in the state of Victoria, Australia. The parsimonious structure of the identified model enhances the model's generalization capability, and it shows the advantages of SDP estimation in providing very descriptive views and interpretations about the interactions and relationships between various components which affect the system's behaviour.

In Chapter 12, Professor David Hendry and his colleague Jennifer Castle consider approaches to the automatic selection of nonlinear models within an econometric context. The strategy is: first, to test for non-linearity in the unrestricted linear formulation; then, if this test is rejected, a general model is specified using polynomials that are simplified to a minimal congruent representation; finally, model selection is by encompassing tests of specific non-linear forms against the selected model. The authors propose solutions to some of the many problems that non-linearity poses: extreme observations leading to non-normal (fat-tailed) distributions; collinearity between non-linear functions; situations when there are more variables than observations in approximating the non-linearity; and excess retention of irrelevant variables. Finally, an empirical application concerned with a 'returns-to-education' demonstrates the feasibility of the non-linear automatic model selection algorithm *Autometrics*.

The theme of model structure selection in nonlinear system identification is continued in Chapter 13 by X. Hong, S. Chen and Professor Chris Harris, this time using radial-basis functions for the modelling of the nonlinear systems. From the angle of the diversified RBF topologies, they consider three different topologies; (i) the RBF network with tunable nodes; (ii) the Box-Cox output transformation based RBF network (Box-Cox RBF); and (iii) the RBF network with boundary value constraints (BVC-RBF). These proposed RBF topologies enhance the modelling capabilities in various ways and it is shown to be advantageous if the linear learning algorithms, e.g. the orthogonal forward selection (OFS) algorithm based leave-one-out (LOO) criteria, are still applicable as part of the proposed algorithms.

0.0.3 Applications of System Identification

Band-pass, Kalman, and adaptive filters are used for the removal of resuscitation artifacts from human ECG signals. Chapter 14 by Professor Ivan Markovsky, Anton Amann and Sabine Van Huffel is a tutorial-style chapter that clarifies the rationale for applying these methods in this particular biomedical context. The novel aspects of the exposition are the deterministic interpretation and comparative study of the methods using a database of separately recorded human ECG and animal resuscitation artifact signals. The performance criterion used in this analysis is the signal-to-noise ratio (SNR) improvement, defined as the ratio of the SNRs of the filtered signal and the given ECG signal. The empirical results show that for low SNR, a band-pass filter yields the best performance; while for high SNR, an adaptive filter yields the best performance.

Professor Eric Rogers and Peter Young have worked for many years on the Editorial Board of the *International Journal of Control*. Chapter 15, by Fengmin Le, Chris Freeman, Ivan Markovsky and Eric, reports recent work involving the use of robots in stroke rehabilitation, where model-based algorithms have been developed to control the application of functional electrical stimulation to the upper limb of stroke patients with incomplete paralysis, in order to assist them in reaching tasks. This, in turn, requires the identification of the response of a human muscle to electrical stimulation. The chapter provides an overview of the progress reported in the literature, together with some currently open research questions.

0.0.4 Data-based Mechanistic Modelling and Environmental Systems

The term *Data-Based Mechanistic* (DBM) *modelling* was first used by Peter Young in the early nineteen nineties, but the basic concepts of this approach to modelling dynamic systems have been developed by Peter and various colleagues over many years. For example, they were first applied seriously within a hydrological context by Peter and Bruce Beck in the early 1970s, with application to the modelling of water quality and flow in rivers, and set by Peter within a more general framework shortly thereafter. Since then, they have been applied to many different systems in diverse areas of application from ecology, through engineering to economics. The next several chapters present various applications, mainly in the area of water resources where DBM modelling, as well as other systems modelling and control procedures, are used to good effect.

From a philosophical standpoint, DBM modelling stresses the need to rely, whenever possible, on inductive inference from time series data, without over-reliance on pre-conceived notions about the structure of the model that can often lead to over-large computer simulation models with severe identifiability problems. Indeed, it was a reaction to such large, over-parameterized models that gave birth to DBM modelling. In Chapter 16, Peter Young briefly outlines of the main stages and procedures involved in DBM modelling. Its main aim, however, is to put the DBM approach to modelling in a philosophical context and demonstrate how this is reflected in an illustrative example, where DBM modelling is applied to the investigation of solute transport and dispersion in water bodies. By providing a *Dynamic Emulation Model* (DEM) bridge between large computer simulation models, produced in a hypothetico–deductive manner, and parsimonious DBM models that are normally identifiable from the available data, it emphasises the need to utilise both approaches, in an integrated manner, in order to meet multiple modelling objectives.

Peter Young's research on flood forecasting techniques based on both rainfall-flow (run-off generation) and flow-flow (flow routing) modelling goes back a long way to the early nineteen seventies. However, since the nineteen eighties it has been heavily influenced by collaboration with his friend and colleague Professor Keith Beven, one of the foremost contributors to the theory and practice of hydrology. In this flood forecasting context, the DBM modeling approach normally identifies a non-linear SDP (see above) transformation of the input rainfall signal that is dependent on the current state (river flow or level) of the system. In Chapter 17, Keith, David Leedal, Paul Smith and Peter, discuss four methods of parameterizing and optimizing the input non-linearity function, each of which have associated advantages and disadvantages: a simple power law; a radial basis function network; piecewise cubic Hermite data interpolation; and, finally, the Takagi-Sugeno Fuzzy Inference method, which employs *human-in-the-loop* interaction during the parameter estimation process.

The *Aggregated Dead Zone* (ADZ) model[1] was one of the first DBM to be developed, initially by Peter Young and Tom Beer in the early nineteen eighties and later by Dr. Steve Wallis, Peter and Keith Beven, who extended it to include the concept of a 'dispersive fraction'. In Chapter 18, Sarka Blazkova, together with Keith Beven and Paul Smith, use the ADZ model for the analysis of tracer data from larger rivers. The model provides excellent explanation of the observed concentrations, with a dispersive fraction parameter that varies relatively little with flow (discharge), making the model applicable over a wide range of flow variations. It is also shown how the information on transport and dispersion at different flows can be augmented by pollution incident and continuously logged water quality data. The model can then be applied to predict the downstream dispersion of pollutants at any arbitrary flow, taking account of the uncertainty in the SRIV estimation (see above) of the ADZ model parameters.

Peter Young has worked with with Drs. Andrea Castelletti and Francesa Pianosi on the DBM modeling of river catchments affected by snow melt. However, Andrea and Francesca, together with Professor Rodolfo Soncini-Sessa are also concerned with the wider topic of water resources management to effectively cope with all the key drivers of global change (climate, demographic, economic, social, policy/law/institutional, and technology changes). Here, it is essential that the traditional sectoral management approach to water resources is transformed into a new paradigm, where water is considered as the principal and cross cutting medium for balancing food, energy security, and environmental sustainability. One major technical challenge, in expanding the scope of water resources management across sectors

[1] Also called the *Aggregated Mixing Volume* (AMV) model when applied in a more general context.

and to the river basin level, is to develop new methodologies and tools to cope with the increasing complexity of water systems. In Chapter 19, Andrea, Francesa and Rodolfo consider the management and control of a large water system composed of reservoirs, natural catchments feeding the reservoirs, diversion dams, water users (e.g. hydropower plants, irrigation districts), and artificial and natural canals that connect all the above components. In particular, they review some of the recent, and in their opinion, more promising alternatives to stochastic dynamic programming in designing sub-optimal control policies.

The theme of river basin management is continued in Chapter 20. Here Professors Rob Evans and Ivan Mareels, together with N. Okello, M. Pham, W. Qiu and S. K. Saleem, point out that river basins are key components of water supply grids. As a result, river basin operators must handle a complex set of objectives, including runoff storage, flood control, supply for consumptive use, hydroelectric power generation, silting management, and maintenance of river basin ecology. At present, operators rely on a combination of simulation and optimization tools to help make operational decisions. However, the complexity associated with this approach makes it unsuitable for real-time (daily or hourly) operation. The consequence is that between longer-term optimized operating points, river basins are largely operated in an open loop manner. This leads to operational inefficiencies, most notably wasted water and poor ecological outcomes. In the chapter, the authors propose a systematic approach for the real-time operation of entire river basin networks, employing simple low order models on which to design optimal model predictive control strategies.

Agriculture is the world-wide biggest consumer of water. However, a large portion of the water is wasted due to inefficient distribution from lakes and reservoirs via rivers to farms. While more efficient water distribution can be achieved with the help of improved control and decision support systems, this requires the identification and estimation relatively simple river models, such as the DBM models used above in river flood forecasting applications. Traditionally, the partial differential Saint Venant equations have been used for modelling flow in rivers but they are not suitable for use in control design and simpler alternative models of the DBM type are required. Such an approach is described in Chapter 21 by Mathias Foo, Su Ki Ooi and Erik Weyer. Based on operational river data and physical considerations, they estimate simple 'time-delay' and 'integrator-delay' models and compare them with the Saint Venant equation model. The efficacy of these simple models is then illustrated in a simulation exercise where they are used to design a control system that is applied successfully to the full Saint Venant equation model.

Professor Howard Wheater, who is very well known for his research and development work in this area, has been one of Peter Young's friends since the nineteen seventies, when both were in different Divisions of the Engineering Department at Cambridge University. Peter has also worked recently with Howard's colleague, Dr. Neil McIntyre, and Howard on the DBM modelling of the non-linear dynamic processes that are active in an experimental catchment. In Chapter 22, Howard, Neil and their colleagues consider the insights developed from Peter's research on DBM modelling in the context of predicting the effects of land use and land management change across multiple scales. This is a particularly challenging problem and they review the strengths and weaknesses of alternative modelling approaches, including: physics-based modelling; conceptual models, conditioned by regionalised indices; and DBM modelling, showing the latter's utility in identifying appropriate model structures that can guide the hydrological application.

It is clear from chapters 19, 20, 21 and 22 that hydrological models have an important role to play in supporting water management. Another important problem in catchment hydrology is river catchment classification. This remains a significant challenge for hydrologists, with available schemes not providing a sufficient basis for consistently distinguishing between different types of hydrological behaviour. However, In Chapter 23, Professors Thorsten Wagener and Neil McIntyre show how the DBM approach to time-series modelling is an eminently suitable approach to this problem since it is designed to extract the dominant modes (signatures) of a system response. They develop a classification procedure based on this idea and apply it to 278 catchments distributed across the Eastern USA, with the aim of exploring whether the catchments may be classified according to their dominant mode responses, including identifying both the type of response (the transfer function structure) and the scale of the response (the associated parameter values). They conclude that the approach holds considerable promise in this kind of application but that more research is required to establish better which of DBM model signatures, or combinations of these, are most powerful in the classification role.

Previous chapters show how the ADZ/AMV models can provide a theoretically elegant and practically useful approach to water quality and pollutant transport modelling that can used both in assessing the risk from pollution incidents and the sustainable management of water resources. An ability to predict the concentrations of a pollutant travelling along the river is necessary in assessing the ecological impact of the pollutant and to plan a remedy against possible damage to humans and the environment. The risk from a pollutant at a given location along the river depends on the maximum concentration of any toxic component, the travel times of the pollutant from the release point and the duration over which its concentration exceeds feasible threshold levels. In Chapter 24, Peter Young's previous research colleague at Lancaster, Dr. Renata Romanowicz (now at the Institute of Geophysics in Warsaw), outlines on-going research on DBM models and compares the results with physically-based approaches using worked examples from pollutant transport modelling. In addition to steady-state examples, a transfer function pollutant transport model for transient flows, that can be interpreted directly in ADZ/AMV terms, is presented and used in a tutorial-style case study on the application of a multi-rate transfer function models to the identification of environmental processes.

Dr. Peter Minchin has known Peter Young since the nineteen seventies, when they worked together on the application of RIV estimation (see above) to the analysis and modelling of phloem translocation data. In Chapter 25, Peter Minchin describes the application of such techniques to the problem of modelling Phloem vasculature within higher plants functions at very high hydrostatic pressure (*circa* 10 atmospheres). A detailed time sequence of phloem sap movement through a plant is possible with in vivo measurement of 11C tracer, which is ideal for input-output transfer function modelling within a DBM context. The resulting estimates of transport distribution times, pathway leakage, and partitioning between competing sinks have led to the first mechanistic understanding of phloem partitioning between competing sinks, from which sink priority has been shown to be an emergent property.

Professor Sivakumar Bellie and Peter Young have maintained contact for some years because of their mutual interest in the use of low order nonlinear models and DBM modelling in environmental systems analysis. In this regard, the last two decades have witnessed a significant momentum in the promising application of *Chaos Theory* (CT) to environmental systems. Nevertheless, there have also been persistent skepticism and criticism of such studies, motivated by the potential limitations in the data-based modelling of chaotic systems. In Chapter 26, Sivakumar offers a balanced perspective of chaos studies in environmental systems: between the philosophy of CT at one extreme, to the down-to-earth pragmatism that is needed in its application at the other. After briefly reviewing the development of CT, some basic identification and estimation methods are described and their reliability for determining system properties are evaluated. A brief review of CT studies in environmental systems as well as the progress and pitfalls is then made. Analysis of four river flow series lend support to the contention that environmental systems are neither deterministic nor stochastic, but a combination of the two; and that CT can offer a middle-ground approach to these extreme deterministic and stochastic views. It is concluded that, in view of the strengths of both CT and DBM concepts (commonalities as well as differences), the coupling of these two data-based modelling approaches seems to be a promising way of formulating a much-needed general framework for environmental modelling.

0.0.5 Control System Design

Peter Young's early research career was concerned with data-based modelling applied in the the context of automatic control system design and he has retained an abiding interest in control system design for the past fifty years. His most novel contributions in this area are concerned with the exploitation of *Non-Minimal State Space* descriptions of dynamic systems based on their estimated transfer function models. This began with early research carried out while he was working as a civilian for the U.S Navy in California and it culminated with a series of research studies beginning at Lancaster in the nineteen eighties and extending to recent research on NMSS-based model predictive control carried out with Professor Liuping Wang at RMIT in Melbourne. In this last section of the book, the first three chapters cover aspects of NMSS and model predictive control system design, while the final one discusses a recently developed MATLAB Toolbox for the analysis of more general state space systems.

The largely tutorial Chapter 27 by Peter Young's long-time colleagues, James Taylor, Arun Chotai and Wlodek Tych, uses case studies based on recent engineering applications, to illustrate the NMSS approach to feedback control system design. The paper starts by reviewing the subject and pointing out that the NMSS representation is a rather natural state space description of a discrete–time transfer function, since its dimension is dictated by the complete structure of the transfer function model. Also, it notes that the resulting *Proportional–Integral–Plus* (PIP) control algorithm can be interpreted as a logical extension of the conventional *Proportional–Integral* (PI) controller, facilitating its straightforward implementation using a standard hardware–software arrangement. Finally, the chapter shows how the basic NMSS approach is readily extended into multivariable, model–predictive and nonlinear control system design contexts and gives pointers to the latest research results in this regard.

Professor Neville Rees and Peter Young have been very close friends for over forty years since they worked together in California between 1968 and 1970. In Chapter 28, Neville and his colleague Chris Lu join with Peter to describe a joint project they have been involved with recently. They briefly introduce the concept of large computer model reduction using dynamic emulation modelling (DEM), as discussed in Chapter 16. SRIV identification and estimation methods (see earlier) available in the *CAPTAIN* Toolbox are exploited to develop a nominal, reduced order DEM for a large Simulink model of a complex, nonlinear, dynamic power plant system, using data obtained from planned experiments performed on this large simulation model. The authors then show how this single, three input, three output, linear emulation model can form the basis for multivariable, NMSS control systems design. The control simulation results cover a wide range of operating conditions and show significant performance improvements in relation to the standard, multi-channel PID control system performance. This is despite the fact that the design is based on the single multivariable model and the simulation model has numerous nonlinear elements.

One of the key components in a renewable energy system, such as wind energy generator, is a three-phase regenerative PWM converter, which is both nonlinear and time-varying by nature. in Chapter 29, Dae Yoo, together with Professor Liuping Wang and another of Peter Young's long-time friends, Professor Peter Gawthrop, consider the model predictive control of such a converter. In particular, with the classical synchronous frame transformation, the nonlinear PWM model is linearized to obtain a continuous-time state-space model. Then, based on this linearized model, a continuous-time model predictive control system for the converter is designed and implemented successfully on a laboratory scale test-bed built by the authors. The proposed approach includes a prescribed degree of stability in the algorithm that overcomes the performance limitation caused by the existing right-half-plant zero in the system. This also provides an effective tuning parameter for the desired closed-loop performance.

The final chapter 30 of this book is written by another former research colleague of Peter Young, Dr. Diego Pedregal, and Dr. James Taylor (see previously). It illustrates the utility of, and provides the basic documentation for, *SSpace*, a recently developed Matlab$^{\text{TM}}$ toolbox for the analysis of State Space systems. The key strength of the toolbox is its generality and flexibility, both in terms of the particular state space form selected and the manner in which generic models are straightforwardly translated into MATLAB code. With the help of a relatively small number of functions, it is possible to fully exploit the power of state space systems, performing operations such as filtering, smoothing, forecasting, interpolation, signal extraction and likelihood estimation. The chapter provides an overview of *SSpace* and demonstrates its usage with several worked examples.

Liuping Wang, RMIT University, Australia.
Hugues Garnier, Nancy University, France.
Tony Jakeman, Australian National University, Australia.

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