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Trends in systems and signals Status report prepared by the IFAC Coordinating Committee on Systems and Signals

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Abstract

This report discusses problems and methodologies that lie in the broad scope of systems and signals, with special focus on modeling, identification and signal processing; adaptation and learning; discrete event and hybrid systems; and stochastic systems. A common theme underlying all these areas is that problems in control systems and signals are usually defined and best studied in the framework of stochastic approaches. Although there are common precepts among all these technologies, there are also many unique topics within each area. Therefore, the current key problems in each technology are explained, followed by a discussion of recent major accomplishments with trends, and finally some forecasts of likely developments are provided. The conclusion summarizes some general forecasts for the overall field of systems and signals.

Keywords: Systems and signals; Modeling; System identification; Adaptive control; Learning; Discrete event systems; Hybrid systems; Stochastic systems

1. Introduction

There are many diverse methodologies that concern systems and signals. This Milestone Report addresses the current status and likely future developments for the following theoretical control techniques and methodologies:

- modeling, identification and signal processing;
- adaptation and learning;
- discrete event and hybrid systems;
- stochastic systems.

There are also many common challenges that all of these control methodologies face, but each with its own unique perspective, e.g., need for improved performance, need for better models, better methods for handling uncertainty, complexity, stability, boundedness, reduction of restrictive assumptions within design methodologies, more applicability to non-linear systems, overcoming random disturbances, improved verification, etc., and certainly the challenge of applying the techniques to real-world applications such as networked systems. However, in order to more clearly address the uniqueness of each of these methodologies, we will discuss the problems, accomplishments and forecasts of each individually in this report.

This paper is organized as follows. In Section 2, we discuss the present status, key problems, recent accomplishment and forecasts within modeling, identification and signal processing. Sections 3–5 are devoted to similar exposition of problems and methodologies in the areas of adaptation and learning, discrete event and hybrid systems, and stochastic systems, respectively. Finally, we conclude the paper in Section 6 with a summary of general forecasts for the overall area of systems and signals.

2. Modeling, identification and signal processing

The objective of modeling and identification technology is to develop efficient techniques which can be used to construct

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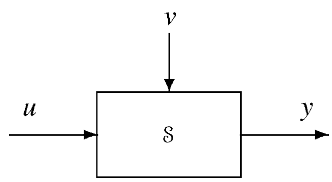

Fig. 1. A system with input u, output y and unmeasured disturbance v.

dynamic models based on physical insight and experimental data. The use of a plant model is crucial for model based control techniques, synthesis of servomechanisms and design of predictive control algorithms, and absolutely every simulation is based on a model of the event or process under consideration. Thus, it is virtually impossible to consider the field of automation and control without including the discipline of modeling. In signal processing, dynamic models are essential in time series analysis, adaptive filtering and fault/change detection, etc. Dynamic models and identification techniques are also critical in many other scientific areas such as econometrics and environmental engineering.

A model of a physical system for developing control solutions should include two main parts: a description of the dynamics from inputs to outputs and a description of the disturbances acting on the system. Fig. 1 shows a standard configuration for open-loop identification, where no feedback exists from y to u. The basic identification problem is to construct a dynamic model of the system based on measured input–output data (u, y). The identification process is satisfactorily solved when the measured data are used to formulate a dynamic model that, when subjected to an input, produces output that ‘‘matches’’ the output of the system when excited by the same input. Most existing control systems are, however, operated in a closed-loop configuration as shown in Fig. 2; in this case we can employ measured input–output data (u, y) together with the reference input r for identifying the plant model. In some cases, the external input can also be measured; this additional information can then also play an important role in successful identification.

2.1. Current key problems

Modeling, identification and signal processing faces many interesting problems; among others, the following are some of the current key problems.

Disturbances in control applications are predominantly described by finite order rational spectral models; yet this type of model is not totally compatible with several other formats used to model stochastic systems. Therefore, the unification of several methods for approximation of stochastic systems with rational spectral disturbance models is an important open problem.

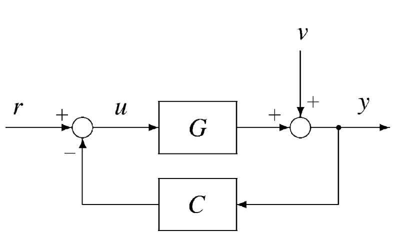

Fig. 2. A block diagram of closed-loop system with plant input u, output y and reference input r.

Since an accurate dynamic model is essential for the design of most controllers, identification should always be seen as an integral part of control design. Therefore, interplay between identification and the designed controller should be utilized when optimizing the design process; see Hjalmarsson (2005). Continued development of methods and analysis tools for control-oriented modeling is therefore another key problem within modeling and identification.

Development of computational Bayesian approaches for both estimation and quantification of modeling errors has emerged only quite recently. Techniques such as Markov Chain Monte Carlo methods have, for example, the ability to provide accurate probabilistic error descriptions for finite length identification data.

The success of many control applications when using linear controllers relies on the fact that the process being controlled behaves like a linear system around an appropriate working point. Clearly this is a limited approach; therefore, identification of non-linear systems using non-linear model structures has been the subject of many studies during recent decades. Nevertheless, this is still a significant challenge for modeling and identification. Since estimation of general non-linear structures from input–output data is quite difficult, we often consider simple combinations of linear dynamics G and a static non-linearity f as shown in Fig. 3. The non-linear models can be used in several ways; examples are detecting the existence of non-linearities or providing non-linear models for use in subsequent non-linear control designs. We have also seen development of approximation of non-linear systems using techniques from machine learning. Examples are neural networks, radial basis functions, support vector machines and reproducing kernel Hilbert spaces, e.g., Perez-Cruz and Bousquet (2004).

2.2. Recent major accomplishments, trends

In the past, a large number of theoretical as well as application papers have been published in the area of modeling, identification and signal processing. The following are major accomplishments in recent years:

(a) Estimation of a rational spectral model from measured data is a classical problem where the maximum-likelihood solution in general leads to minimization of a possibly non-convex criterion. Hence, non-iterative computational techniques are of practical interest. Recently two different techniques have emerged which provide promising alternative solutions to the

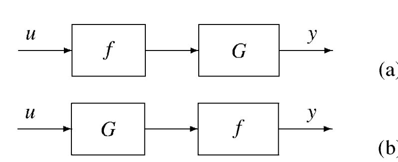

Fig. 3. Non-linear models: (a) Hammerstein model and (b) Wiener model.

problem. The first uses sample covariance matrices estimated from data and then finds a valid stochastic model which extends the sample covariance sequences; see Byrnes, Gusev, and Lindquist (1999). A second approach presented by Mari, Stoica, and McKelvey (2000) finds a valid stochastic model which approximates the given sequence of sample covariances.

(b) Use of computational Bayesian approaches for estimation and a posteriori quantification of model errors has proved to be accurate and useful for our domain of problems; see Spall (2003) and Doucet and Wang (2005). The Bayesian technique forms a statistically sound basis where the a priori knowledge and the data together provides the *a posteriori* estimate of the system.

(c) Utilizing subspace methods for data collected under feedback is now much better understood, and recently several new techniques have been presented by Katayama, Kawauchi, and Picci (2005), Qin, Lina, and Ljung (2005) and Chiuso and Picci (2005). In Bauer (2005) a uniform analysis of the asymptotic properties of subspace methods is presented. Using discrete Fourier transformed data in subspace methods has provided good results for deterministic systems. Recently, also algorithms for stochastic and combined system are emerging, e.g., Akcay and Türkay (2004).

(d) Plant friendly identification is a name for techniques aimed at resolving the inherent conflict between theoretical results on how to best achieve high quality models and the requirements of the plant operation from a production point of view. This topic is very relevant for industry, and we have seen some developments of both theory and methods which also encompasses relevant input constraints, e.g., Jansson and Hjalmarsson (2005) and Kammer, Gorinevsky, and Dumont (2003).

(e) For control design it is vital to assess the frequency domain errors induced by the noise. In Ninness and Hjalmarsson (2004) exact variance expressions are derived for the case of a general finite order Box-Jenkins model.

(f) Modeling of non-linear dynamic systems has always attracted significant attention since many phenomena have significant non-linear contributions. Currently the primary interests can be divided into three approaches: (1) approximation of Volterra series models, e.g., Nemeth, Kollar, and Schoukens (2002), (2) estimation of Hammerstein and Wiener systems, e.g., Goethals, Pelckmans, Suykens, and De Moor (2005), and (3) non-linear regression based models, e.g., Roll, Nazin, and Ljung (2005).

The Volterra approach has the advantage of a close connection with linear analysis and provides a good structure to analyze and quantify small to moderate non-linear contributions. The second estimation technique involves a mixture of linear model identification and static non-linear function approximation. Non-linear regression approach is closely related to machine learning and several methodologies have been adapted to the time series setting. Key current methodologies are support vector machines, neural networks, reproducing kernel Hilbert spaces, etc. Most often linear time-invariant models are identified although the system is non-linear and time-varying. Analysis of this setting has appeared in, e.g., Ljung (2001), Schoukens, Pintelon, Dobrowiecki, and Rolain (2005) and Mäkilä and Partington (2004).

2.3. Forecast

Although modeling and identification have been useful tools during all of the ‘‘modern control’’ era, there are still significant challenges to be addressed as control technology advances and complexity of applications increase. This discipline will continue to advance, and several developments can be expected within the coming years:

(a) In the future, we expect powerful new linear system identification tools such that large scale systems can efficiently be modeled. Here ‘‘large scale’’ refers to model orders of 50–1000 states and inputs and outputs in the order of 10–100.

(b) In many cases, a well posed system identification problem leads to minimization of a possibly non-convex criterion function. However, we expect new global search strategies which incorporate problem domain knowledge to thereby improve performance and reduce computational requirements; such developments should come within the next few years. Examples of such developments are interval analysis and grid based methods combined with branch and bound techniques.

(c) Many alternative modeling techniques will develop in the future as a result of on-going decreases in the price for data storage. The ability to store large quantities of operational data opens up many new alternative possibilities for modeling. A database where all operational records are stored could then form the basis of the model. When a particular feature is requested of the model, it can be estimated on-line by querying the database for relevant data. Several interesting problems will arise such as how the operational data will be organized and how queries to the database should be constructed. It will also be important to find methods, i.e., data mining techniques, which automatically evaluate the information content in data. Today latent variable methods like principal component analysis (PCA) and partial least squares (PLS) are used to project data to a lower dimensional subspace where analysis and control can be applied.

(d) The use of randomization methods for solving estimation and filtering problems is expected to increase significantly in the future. These methods will also provide the ability to accurately predict performance of estimated models.

(e) Almost all identification methods use optimization techniques to calculate the parameter estimates. In some applications, the model class should be constrained due to physical reasons. The use of semi-definite programming techniques will help solve many such problems.

(f) It is apparent that as advances are made within computer and signal processing technologies, many tasks which

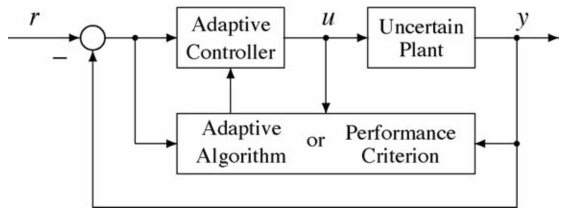

Fig. 4. A configuration of adaptive control system.

require manual processing will be automated so that intervention by an operator will be reduced, or even eliminated. There are several efforts underway within modeling and identification that are aimed towards development of ‘‘automatic’’ identification methods, and we should see continued progress in this direction in the future.

3. Adaptation and learning

Adaptation and learning methodologies are especially useful to attain high performance of control systems which operate in *uncertain situations*. These control methods are intended to deliver proper system operation in spite of unknown – or unpredicted – circumstances, in unforeseen environments or even in situations where unexpected change may occur within the plant being controlled. In past decades, adaptation and learning approaches have been developed from various theoretical and application points of view. Although it seems that the number of *theoretical* papers presented in recent IEEE conferences, and various IFAC meetings is shrinking, the number of *application* papers is increasing; thus, practical applications are obviously spreading into various areas of industry. Actually much more papers on adaptation and learning appear in application sessions.

As shown in Fig. 4, adaptive control systems have two feedback loops: one is the adaptation loop for updating controller parameters and the other is the feedback control loop. The global stability can be attained by both the stability of the adaptation algorithm and the boundedness of internal states of the feedback control system; thus, the stability assurance is an important issue of adaptive control for long time.

As shown in Figs. 5 and 6, the adaptive structures adopted in adaptive signal processing and adaptive control are different, in which the connection of unknown system and adaptive system is reversed. Stabilization of the structure in Fig. 5 is easily

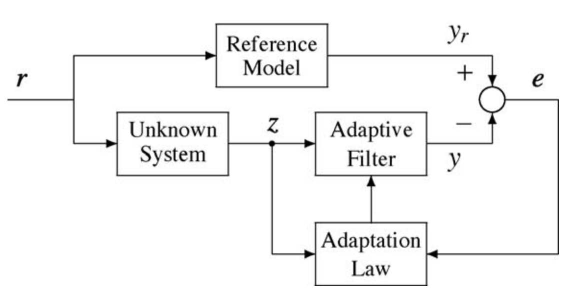

Fig. 5. A block diagram for adaptive filtering.

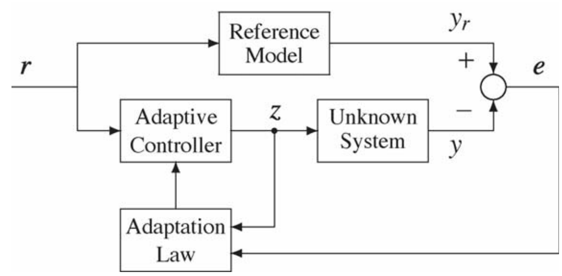

Fig. 6. A block diagram for adaptive control.

attained, so actually adaptive filtering and equalization is effectively adopted in signal and communication areas.

3.1. Current key problems

Although adaptive and learning control techniques have been under development for many years, there are still significant challenges being addressed by both researchers and practitioners. Current key problems and trends are summarized as follows.

Adaptive control schemes with assurance of stability and boundedness of internal states are limited to only certain classes of control systems. This is an interesting situation in which there are demonstrated successful practical applications for which there are no theoretical ‘‘proofs’’ that such problems will in fact be stable. Some researchers have suggested that this may be part of the reason that theoretical interest may be declining; these techniques may simply apply to more diverse applications than can be fully supported by theory. Clearly additional theoretical research is needed to expand the classes for which stability can be proven; thus, relaxation of the necessary conditions and extension to even more general classes are still to be investigated. These investigations are, for instance, (a) achieving robustness in the presence of unmodeled dynamics and unknown disturbances together with assurance of global or local stability, (b) eliminating the necessity of prior information on the relative degree of controlled systems, or establishing robust adaptive control algorithms for systems with uncertain relative degree, (c) extending applicability of globally stable adaptive control schemes limited to linear systems with a stable numerator or non-linear systems with stable zero dynamics, (d) giving stability-assured adaptive control schemes for time-varying systems, (e) developing adaptation approaches to control of systems with uncertainly changeable delay time, etc.

Adaptive control methods for non-linear systems are still major research themes since almost all systems include some non-linearities. The following issues are currently discussed for non-linear adaptive control:

(a) Stable adaptive control for canonical forms of non-linear systems is developed based on new stability analysis.
(b) Extension of linear parametrization to non-linear parametrization is an important issue, in which unknown parameters appear non-linearly in input/output or in states.
(c) For a wide class of non-linear control systems, it seems difficult to give general adaptive control algorithms in analytic form and implement them in a feasible manner

even if they can be given. Some simplified approaches are made by adopting multiple models of fixed or adaptive controllers or by switching multiple controllers. Stability analysis is also made for the multiple model approaches.

(d) Neural network based adaptive control algorithms are also theoretically investigated from stability points of view as well as practical applications.

Several adaptive algorithms have been proposed, for instance, extended error method based on the certainty equivalence (CE) principle, high-order tuning method based on the dynamic equivalence principle, and the backstepping method. It is important to attain fast adaptation and suppressed transient error, and then an evaluation method of the transient error bound is needed to decide design parameters for the adaptive algorithm. Furthermore, adaptive control schemes should give suitable guidelines for design of adaptive control systems to attain desirable transient behavior and optimal performance.

One of the major themes in the area of adaptation and learning is iterative learning control or repetitive control. With the help of least prior knowledge on a controlled system, the controller can be iteratively updated so that the system output can track a periodic or repetitive reference signal. Convergence analysis is investigated and its applicability is now extended to non-linear controlled systems. The iterative learning control algorithms have advantages of simplicity in implementation for uncertain non-linear systems.

As alternative non-model based control approach, data based control system design methods are much efficient, which is referred to as lazy-learning control, local model based control, just-in-time control or query based control. The approaches are also applied to system identification and output prediction for non-linear systems. The more the database is increasingly obtained, the better control performance can be attained, compared to neural network controllers.

On of the most significant efforts underway in adaptive and learning field is extension and expansion of applications to an even wider variety of practical systems: mechanical systems, mechatronics, robotics, automobile, intelligent traffic systems, aerospace, nanotechnology, manufacturing, smart structures, chemical processes, iron and steel processes, environmental control systems, wireless communications, signal and image processing, network control, etc. Part of the challenge is for engineers and scientists to continue to develop additional practical applications even into situations where a strong theoretical justification may not exist.

3.2. *Recent major accomplishments and trends*

Adaptive and learning techniques have made dramatic progress in the last few decades, and practical applications are now being developed in many fields. Current research is especially focused on applying the methodologies to even more practical solutions. However, two major theoretical accomplishments are apparent:

- Relaxation of necessary assumptions so that wide class of systems can be adaptively controlled.
- Quality design and implementation of adaptation and learning algorithms.

3.2.1. *Extension of the classes of controlled systems and relaxation of necessary assumptions*

A variety of robust adaptive control schemes have been developed to assure global stability of the controlled system even in the presence of unmodeled dynamics and disturbances. The normalization or normalizing signal is needed in the error dynamics to assure the boundedness, and its mechanism is also clarified. However, the role of the normalizing signals is not yet clarified in a case with dynamic error systems.

Prior knowledge on the relative degree of a controlled process is assumed in almost all adaptive design schemes. This is because the most theoretical results on stability are based on passivity. However, exact relative degree is usually unknown in actual control processes. A new backstepping based adaptive algorithm has been derived to attain robustness on the relative degree; e.g., see Miyasato (2000). The ‘‘immersion and invariance approach’’ in Astolfi and Ortega (2003) gives a new adaptation algorithm based on a new tool of stability analysis and it is also shown to be robust to uncertainty in the relative degree. The relative degree is a very restrictive condition in stable adaptive controller design, so it is still an open problem.

Non-minimum phase systems or stable zero dynamics is a necessary assumption to obtain stable control performance for the model reference adaptive control systems (MRACS). In order to relax these assumptions, alternative adaptive control schemes have been formulated and solved, such as adaptive pole assignment control, model predictive control and others.

An effective backstepping approach has been developed to attain adaptation performance of a class of non-linear systems. It can be extended to a certain case with unknown disturbances based on the internal model principle. Local and global conditions on stability are discussed on a wider class of non-linear control systems. These theoretical approaches also have an impact on stable design of neural network (NN) based adaptive control systems.

Conventional adaptation and learning control schemes assume that the unknown parameters are time-invariant and appear in a linear parametrization form. Several recent methods address alternative cases. When the system parameters appear in a convex or concave with respect to them, a new efficient adaptive adjustment law in Cao and Annaswamy (2003) has been given to assure global stability of the obtained system. Alternatively, by expressing an upper bound of non-linear function of parameters and states as a product of parameters and non-linear state functions, a very simple adaptation law is also derived. The immersion and invariance approach is also effective to cope with non-linear parametrization.

3.2.2. *Quality design and implementation of adaptation and learning algorithms*

In order to improve transient behavior of adaptive control systems, some approaches for evaluation of an upper bound of the output error have been proposed, and it has clarified the dynamic relations between the output error and the design parameters of the control systems, which will give help to achievement of adaptation with optimal transient behavior. Adaptation also plays a very important role as adaptive filtering in signal processing and wireless communication. In the adaptive signal processing area, a new tool for more precisely evaluating the transient behavior of adaptive filters, referred to as a learning curve, has been developed in Yousef and Sayed (2001).

Ordinary adaptive control schemes are limited to model reference adaptive control system, self-tuning regulator (STR) and self-tuning controller (STC). Recently adaptive extremum seeking control problems are formulated for minimization of a non-linear performance index including unknown design parameters subject to an uncertain non-linear dynamic system; e.g., see Krstic and Wang (2000) and Rotea (2000). Several approaches have been made, such as a perturbation approach, passivity based approach, Lyapunov based approach and sliding-mode based scheme. The scope of adaptive control is therefore now extended to adaptive optimization.

Combination of adaptation and learning approaches with iterative learning control (ILC), iterative feedback tuning (IFT), iterative procedure of identification and controller design has been studied. Since these approaches adapt to actual control system design, many works have been done on the topic. The ILC has seen major developments in the transfer of design algorithms using various methods to both engineering and non-engineering applications together with the emergence of the basis for a robust control theory. As for IFT, theoretical results have been obtained on model-free tuning of controllers in an iterative experimentation and controller recalculation process, using direct evaluation of input–output data to obtain the empirical gradients of the controller cost function. The result were demonstrated in a few industrial applications as well as on laboratory hardware. This controller tuning method is likely to spread in industrial applications because of its direct experimental approach that conservative industry is more willing to accept. Also, preliminary investigations show a possibility of tuning for robustness without explicit plant modeling.

An alternative non-model based approach to uncertain non-linear systems is query based adaptive control which is also referred to as lazy-learning control, just-in-time control. The approach needs a large database for learning prior to control, but its concept and algorithm are very simple and will be one of powerful learning control schemes to uncertain non-linear systems. However, its theoretical investigation has not been developed yet and should be done as a future issue.

Dual control is an old, but still open problem. The overall performance is given by compromise between fast identification and control quality. Recently promising results have been obtained for laying down the fundamentals of worst-case dual control, on finite time tuning schemes and the development of stochastic predictive dual control that has combined features of caution, probing and constraint handling simultaneously; see Veres (1999). A bicriterion approach was developed by using a learning weight to define a compromise between the immediate control effect and the learning effect of the controller.

Adaptation and learning approaches for robust control design have also been studied. Many results are reported on identification of unmodeled dynamics by using a finite number of input–output data from various points of view, such as the stochastic learning approach. Adaptive control approaches are now linked with robust control schemes, such as gain scheduled control, sliding mode control and others. The number of papers and case study reports and industrial applications of adaptation and learning approaches is increasing. The effectiveness of adaptation and learning approaches when applied to robust control is now being more widely recognized. However, a universal design guideline is not clarified yet; it is only considered on a case-by-case basis.

3.3. Forecast

Although adaptation and learning are fairly mature technologies within the control field, continued development is expected. Theoretical developments may not be as active as in past decades, but practical applications of these technologies will no doubt experience the most growth.

Adaptation and learning approaches to non-linear systems are still very important issues and will be further developed. New adaptive algorithms with guaranteed stability and novel control schemes will be further developed. Experiment based iterative approaches and dual control to handle transients are likely to be developed further. Query based control may go through some growth in control of a wide class of non-linear systems. Neural network based control will receive an ever more advanced theoretical investigation from researchers from stability point of view. Also, more techniques are expected to appear to integrate neuro-fuzzy techniques with traditional structured model and logic based approaches.

Many case studies have been reported, but actual industrial applications are not yet as common as they will likely become. However, since the effectiveness of adaptive approaches is clear compared to robust control schemes, the applications will no doubt spread in various areas along with developments of design guidelines for adaptation and efficient combination of other control approaches, such as the linear-quadratic-Gaussian (LQG) control, H_∞ robust control, gain scheduled control, sliding mode control and others. Application area will spread in future, for instance, adaptive control of large scale systems, decentralized adaptive control, adaptive control of large communication network with variable delay times, as well as adaptive control of micro- or nano-scale systems.

4. Discrete event and hybrid systems

Fig. 7 contrasts the typical behavior of time-driven and event-driven systems, in which the dynamics of the time-driven system are governed by a differential (difference) equation, whereas those of the event-driven system (with four states in the example shown) are controlled by signals or triggers due to occurrences of various events. This type of dynamic behavior is important as it typifies most modern technological systems, such as those encountered in manufacturing, computer

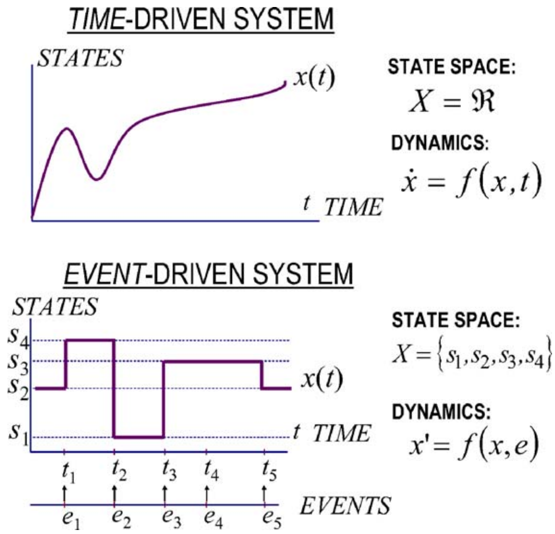

Fig. 7. Time-driven and event-driven systems.

networking, transportation, command-control and, more generally, settings that involve the use of computers for control purposes.

4.1. Current key problems

The most broad based general problem is that of integrating the theories of discrete event systems (DES) [see Cassandras & Lafortune, 1999] and hybrid systems (HS) [see Antsaklis, 2000, and selected chapters in Levine & Hristu, 2005] that would result in a comprehensive unifying system and control theory incorporating both time-driven and event-driven dynamics. Efforts along these lines are impeded by the fact that few researchers have complete command of both the DES framework and the classical time-driven theory, which have traditionally evolved somewhat independently.

In DES, two major current problems are those of decentralized supervisory control, e.g., Rudie and Wonham (1992) and Sic and Lafortune (2005), and control with imperfect information, e.g., Park and Lim (2000). In the latter case, research has been directed along the lines of studying uncertainty in the sense of robustness (i.e., studying the effect of perturbations in model parameters), as well as using stochastic models and methods.

Another problem of interest to DES is that of controlling concurrency, i.e., two DES or two components of the same DES that involve concurrent events, e.g., Takai and Ushio (2003).

A key challenge in developing workable solutions to problems in DES is that of computational complexity, e.g., Rudie and Willems (1995) and Sampath, Sengupta, Lafortune, Sinnamohideen, and Teneketzis (2004). This is an unavoidable byproduct of the presence of discrete components in a DES modeling setting, and one that is naturally inherited by HS as well. This gives rise to the problem of abstraction: can a DES be found that preserves certain desirable properties of a HS, e.g., Alur, Henzinger, Lafferriere, and Pappas (2000) and Silva and Krogh (2000)? If so, problems related to the HS can be analyzed through a simpler DES model. Interestingly, the converse problem is also of great interest: can a simple HS be identified that preserves certain desirable properties of a complex DES? A noteworthy example is the Internet, which, being a communication network, is a typical DES. Because of its complexity, it is desirable to abstract it into a simpler model which is hybrid in nature, i.e., it is characterized by time-driven dynamics with interspersed discrete events, e.g., Cassandras, Wardi, Melamed, Sun, and Panayiotou (2002).

A related problem of great importance to both DES and HS is that of controller verification: given a particular specification and a controller designed to satisfy it, what are formal methods through which one can verify that this is indeed the case, e.g., Alur, Henzinger, and Ho (1996), Silva and Krogh (2000) and Tomlin, Mitchell, Bayen, and Oishi (2003)?

In developing a theory for HS that parallels that of classical time-driven systems, one faces the usual problems of traditional system and control theory: observability, controllability, stability, identification and optimal control.

A fundamental problem in both DES and HS is that of process synchronization. These systems commonly involve multiple asynchronous interacting processes. Imposing a synchronizing mechanism is difficult and occasionally ill-advised. Developing distributed control mechanisms is highly desirable, but generates instabilities that can be overcome either through explicit synchronization schemes (often inefficient) or through new mechanisms with inherent stabilizing properties.

A related problem is that of converting sampling and control mechanisms from time-driven to event-driven. Not only is this a theoretically challenging issue that parallels the contrast between Riemann (time-driven) and Lebesgue (event-driven) integration (Åström & Bernhardsson, 2002), but the benefits of event-driven schemes in emerging wireless power-limited systems are potentially enormous.

4.2. Recent accomplishments, trends

A problem coming under the heading of a ‘‘DES with imperfect information’’ is that of fault diagnosis. In simple terms, when an undesirable state is entered in a DES (a ‘‘fault’’ occurs), the issue is to identify the sequence of events that led to a transition to this state and hence the cause of the fault. This problem has attracted a lot of attention from the DES community and significant progress has been made in the form of explicit models for representing processes with faults captured as ‘‘events’’ and supervisory control techniques for diagnosing the source of such faults, e.g., Lafortune, Teneketzis, Sampath, Sengupta, and Sinnamohideen (2001), Sampath, Sengupta, Lafortune, Sinnamohideen, and Teneketzis (1996) and Jiang, Huang, Chandra, and Kumar (2001).

Significant progress has also been made in the effort to develop unified modeling frameworks for integrating the theories of DES and HS. Specifically, extending the classical setting of state automata used in DES, hybrid automata have gained popularity in dealing with HS, e.g., Johansson, Lygeros, Zhang, and Sastry (2000). However, there are still many alternative models proposed and the final word on which of those will ultimately gain universal recognition has not yet been written. A recent workshop [June 23–26, 2003, Veldhoven, The Netherlands] on ‘‘Modeling and Control of Hybrid Systems’’ is a good reflection of the state of the art.

Perhaps the simplest class of HS is that of linear switched systems. Such systems have been the focus of research work originating both from the classical control theory community which views them as standard linear systems with occasional changes in the model parameters, as well as from the DES community which views them as hybrid automata.

A recent trend in the analysis of HS is an effort to design continuous signal to finite symbol mappings. This leads to symbolic descriptions and methods for system control, including coding in finite-bandwidth control applications and applying formal language theory to the continuous system domain. An upcoming special issue of the *IEEE Transactions in Automatic Control* will be dedicated to this topic.

Clearly, a major driving force behind recent developments in DES and HS is the complexity of these systems. Therefore, ongoing work has been geared towards understanding complexity and overcoming it through a variety of novel (and sometimes not-so-novel) approaches. Related to this development is a trend towards using quantization in control. Another related development is the use of receding horizon concepts dealing with optimal control problems in DES and HS.

Despite all these developments, practical tools for designing and analyzing DES and HS are still lacking. Several efforts along these lines are ongoing both in academic environments and industrial organizations, including the development of new simulation tools for HS.

DES and HS are at the center of a trend towards what is now referred to as the convergence of communications, computing and control. The study of networked control systems is an emerging area expected to thrive over the next few years. An upcoming special issue of the *IEEE Transactions in Automatic Control* is dedicated to this topic.

4.3. Forecast

The field of DES has reached a level of considerable maturity in terms of modeling frameworks. In contrast, researchers in HS are continuing to experiment with different models and one can expect that this process will continue for a few more years. Models that efficiently unify HS and DES will eventually emerge.

As increasingly more complex systems continue to be designed, the problem of fault diagnosis is likely to remain at the forefront of DES research. The use of state automata and supervisory control techniques with partial information will continue to be one of the most attractive approaches to fault diagnosis.

The need for software tools to analyze DES and HS, perform controller synthesis and verification, and evaluate the performance of such systems will drive significant growth in this area. Both industrial and academic communities have already invested a considerable amount of effort in this direction. Recently, for instance, the popular Simulink© time-driven simulation software environment was enhanced by SimEvents, an event-driven simulator, thus providing a new general-purpose commercial product for hybrid system simulation. The next few years are likely to see a number of competing tools and a process of ‘‘natural selection’’ among them.

In the HS domain, switched linear systems have attracted a lot of attention, largely because they allow many of the standard results in linear systems to be extended and adapted to switched control with relatively little effort. However, such activity provides little innovation and it is likely that this trend will rapidly bring about natural saturation. A more promising growth area is that of symbolic descriptions and methods for control, and one can expect it to generate much more interest over the next few years.

The issue of system ‘‘complexity’’, as a concept that demands deeper understanding and extensive intellectual exploration, is likely to dominate the theoretical agenda of many research groups in the DES and HS fields. This will also naturally bring closer control theory and computer science.

Emerging technologies are inevitably the drivers for many of the activities in the DES and HS fields. Whereas manufacturing was one of the prevalent application areas in the 1980s and 1990s, communication networks and computer systems now provide a much broader and rapidly evolving playground for DES and HS researchers. Embedded systems and sensor networks are the latest developments that will foster the long anticipated convergence of communications, computing and control.

5. Stochastic systems

Stochastic systems represent a flexible modeling tool for describing dynamic behaviors in presence of uncertainty and are successfully used in many estimation, identification and control problems.

Stochasticity is not only a tool for modeling reality, however. It is also a desirable ingredient that is artificially introduced in many problem set-ups to improve solvability. This is, e.g., the case of randomized methods in optimization, robust control and blind deconvolution, to cite but a few examples. Thus, stochastic system theory delivers valuable and successful methodologies for modeling real systems and processes as well as for finding solutions in many different engineering endeavors.

5.1. Current key problems

The field of stochastic systems presents many challenging problems; without any attempt of completeness, the following are some of the key problems today:

Modeling and control of complex stochastic systems: Complex stochastic systems include large, hybrid, event-driven and discrete event systems; see Cassandras, Pepyne, and Wardi (2001), Bemporad and Di Cairano (2005) and Cassandras and Lafortune (1999). Complex systems deliver challenging problems both in system identification and in control that go well beyond traditional difficulties and involve converging aspects in communication, control and computation.

Goal-oriented system identification: When performing identification, the final use of the model has to be kept in mind and the model quality has to be judged in relation to the intended use of the model. In particular, designing identification methodologies that are geared towards the synthesis of control units is a challenging key problem today. See Gevers (2000) and the recent survey, Hjalmarsson (2005).

Subspace methods system identification: Subspace methods are used for the identification of systems described in a state-space form; see, e.g., Katayama (2005). One important challenge the identification community is facing is that of incorporating a priori knowledge in subspace system identification methods. Moreover, closed-loop subspace identification is not completely understood yet; see Chiuso and Picci (2005).

Robust (worst-case) decision making (e.g., robust controller selection) through randomized methods: Many robust decision making problems are difficult to solve because of their computational complexity and no algorithm that scales polynomially with the problem size is available. A way to escape such a difficulty is to resort to randomized methods: a multisample of instances of the uncertain parameter is randomly extracted and a decision making problem where these instances only are taken into consideration is solved (see Fig. 8). The so-found solution should have 'generalization properties', that is, it is robust even towards unseen uncertainty instances. First achievements along this line have been achieved in Calafiore and Campi (2005, 2006), but the potentials of this approach are expected to go well beyond what has been so far discovered.

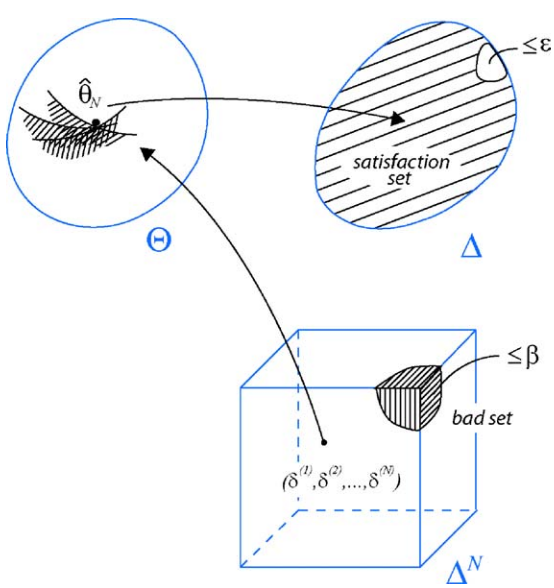

Fig. 8. The sampling mechanism of randomized methods for robust (worst-case) optimization, where Δ is the uncertain parameter set, Δ^N the set where extraction of the multisample is performed and Θ is the set of optimization variables. The 'satisfaction set' is the set of uncertain parameters towards which robustness is automatically guaranteed.

5.2. Recent major accomplishments, trends

Stochastic systems have a long and rich history in the science of modeling real phenomena, with goals ranging from system description to prediction of future events and from decision making in presence of uncertainty to plant control.

5.2.1. Stochastic modeling of complex systems

Stochastic modeling is nowadays moving towards the description of systems of progressively increasing complexity. This includes:

(a) large scale systems,
(b) systems with decentralized control units,
(c) hybrid and event-driven stochastic systems,
(d) systems with communication constraints,
(e) hidden Markov models.

The mathematical description and use of systems belonging to either of the above listed categories involves specific challenges. Regarding large scale systems, advances have been made in recent years in the description of: (a.1) complex manufacturing systems (e.g. semiconductor manufacturing) and (a.2) large scale communication networks (e.g., WWW) (Alpcan, Basar, & Tempo, 2005).

Fields of intense research activity within systems with decentralized control units are: (b.1) wireless ad-hoc networks; (b.2) vehicle traffic control (ground traffic-highways, Giridhar & Kumar, 2006; Varaiya, 2005; airplane traffic, see the Hybridge website: http://hosted.nlr.nl/public/hosted-sites/hybridge).

Hybrid and event-driven (including jump parameters) stochastic systems are gaining increasing popularity mainly for their versatility in accommodating diverse needs in a number of modeling contexts. Systems with communication constraints have become a hot research subject since constraints and delays in communication are important aspects for highly performing distributed systems. Finally, hidden Markov models (Elliott, Aggoun, & Moore, 1995) are being used in many application problems, including image and speech processing as well as some recently emerging areas such as genome analysis.

Despite the recent progresses in the above listed modeling fields, it appears that a long road is still to be covered and, in certain cases, that only the tip of the iceberg has been as far unveiled.

5.2.2. System identification

Recent years have witnessed a resurgence of interest in some traditional topics in stochastic system identification, as well as the birth of new challenging aspects of this discipline. A list of subjects in system identification of present interest that have witnessed important accomplishments in the last few years is the following:

(a) identification of hybrid systems;
(b) identification for control;
(c) subspace methods;
(d) learning theory;
(e) finite sample results for system identification.

While points (a)–(c) have been described elsewhere in this paper, we limit to say that point (e) refers to an emerging area in system identification where finite sample guaranteed results – as opposed to results that only hold asymptotically – are sought after; see Campi and Weyer (2005). Learning theory, point (d), is an independent subject in statistics aimed at establishing the intrinsic limits in the process of learning from data and has important connections with finite sample system identification; see Vapnik (1996) and Vidyasagar (1997).

5.2.3. Randomized methods

Randomized methods refer to the body of solution methodologies where probability is deliberately introduced as an algorithmic tool to solve problems that would otherwise be too complicated to tackle along standard deterministic ways; see Tempo, Calafiore, and Dabbene (2005). Examples where randomized methods are used include:

(a) decision making along an average approach (e.g., average robust controller selection);
(b) evaluation of probability of events;
(c) worst-case decision making (e.g., worst-case robust controller selection).

Decision making along the average approach has been given increasing attention by the scientific community in the last few years and is today a relatively mature subject that presents significant connections with the statistical learning literature; see Vidyasagar (2001). Evaluation of probability of events goes back to standard Monte Carlo methods, but new significant accomplishments have been obtained recently in connection with the evaluation of the probability of rare events, that is, events that occur under rare circumstances only; see, e.g., Del Moral (2004) and Glasserman, Heidelberger, Shahabuddin, and Zajic (1999). Finally, worst-case decision making with randomized methods is a truly new and promising subject area.

5.3. Forecast

Specific efforts will be spent in the next few years towards solving the key problems for stochastic systems as explained earlier. Specifically, it is observed that new problems involving complex stochastic systems spring up almost daily and a special effort is therefore expected in the direction of new methodologies for handling systems of this type. Moreover, randomized methods for robust decision making look very promising and are expected to attract a good deal of attention in the near future.

System identification will continue to attract the attention of a vast community in the coming years and the research is expected to be directed towards a broad range of subjects, including subspace methods, control-oriented identification and finite sample identification. A potentially promising subject within system identification is the use of randomized algorithms aimed at delivering probabilistically guaranteed confidence regions for the estimated models.

As a final remark, we wish to note that the control community has today the opportunity to contribute not only to traditional but also to less traditional fields involving stochastic systems. This includes research subjects in biology, communication, effect–cause inverse problems, computational vision, decision making in management and finance. It is important that our community be able to take up these new challenges in the upcoming years.

6. Conclusions

We have discussed the major problems, accomplishments and forecasts of likely future developments of a broad class of systems and signals. Controller methodologies applicable to systems and signals have played important fundamental roles in analysis and design of various control systems, and will continue to be the central issues of automatic control for many years to come. As we close, the following general forecasts can be visualized for this field:

(a) First, we can be confident that developments of advanced communications and networks which have occurred within the last decade are going to have a significant impact on future control systems. However, methodologies that have traditionally been associated with control will likewise contribute to further advancements within the communications and network field. The future will see many synergistic benefits coming from joint developments of these two fields.
(b) Subspace identification methods will play important roles in the identification in closed-loop systems, and some up-to-date knowledge and procedures of closed-loop subspace identification will be discussed at the 2005 Prague IFAC Congress. Also, identification of non-linear systems will receive much attention in the future, including Wiener and Hammerstein models, for which kernel methods, support vector machine, neural networks and radial basis functions are employed.
(c) Adaptation and learning approaches to non-linear systems are still very important issues and will be further developed. Also, many case studies have been reported, but actual industrial applications are not as common. Applications will spread in various areas along with developments of design guidelines for adaptation and efficient combination of other control approaches.
(d) Discrete event systems and hybrid systems are at the center of a trend towards what is now referred to as the convergence of communications, computing and control. The study of networked control systems is an emerging area expected to thrive over the next few years. Moreover, efforts for developing practical tools for designing and analyzing DES and HS will be done both in academic environments and industrial organizations, including the development of new simulation tools for HS.
(e) New problems involving complex stochastic systems spring up almost daily and a special effort is therefore expected in the direction of new methodologies for handling systems of this type. Randomization methods for robust decision making look very promising and are expected to attract a good deal of attention in the near future. A promising

subject within system identification is the use of randomization algorithms aiming at delivering probabilistically guaranteed confidence regions for the estimated models, including finite sample identification.

(f) As mentioned above most future topics require some sort of probabilistic or stochastic concepts in modeling and control of large complex systems. Thus, we believe that robust design in the future will be based on stochastic techniques, including stochastic robust techniques and randomization approaches.

References

Akcay, H., & Türkay, S. (2004). Frequency domain subspace based identification of discrete-time power spectra from nonuniformly spaced measurements. *Automatica, 40*(8), 1333–1347.

Alpcan, T., Basar, T., & Tempo, R. (2005). Randomized algorithms for stability and robustness of high-speed communication networks. *IEEE Transactions on Neural Networks, 47*(5), 1229–1241.

Alur, R., Henzinger, T. A., & Ho, P. H. (1996). Automatic symbolic verification of embedded systems. *IEEE Transactions on Software Engineering, 22*(3), 181–201.

Alur, R., Henzinger, T. A., Lafferriere, G., & Pappas, G. J. (2000). Discrete abstractions of hybrid systems. *Proceedings of the IEEE, 88*(7), 971–984.

Antsaklis, P. J. (Ed.) (2000), Special issue on hybrid systems. *Proceedings of the IEEE*, *88*(7), 879–887.

Astolfi, A., & Ortega, R. (2003). Immersion and invariance: A new tool for stabilization and adaptive control of nonlinear systems. *IEEE Transactions on Automatic Control, 48*(4), 590–606.

Åström, K. J., & Bernhardsson, B. M. (2002). Comparison of Riemann and Lebesgue sampling for first order stochastic systems. In *Proceedings of 40th IEEE conference on decision and control* (pp. 2011–2016).

Bauer, D. (2005). Asymptotic properties of subspace estimators. *Automatica, 41*(3), 359–376.

Bemporad, A., & Di Cairano, S. (2005). Optimal control of discrete hybrid stochastic automata. In M. Morari, & L. Thiele (Eds.), *Hybrid systems: Computation and control. Lecture notes in computer science* (pp. 151–167). Springer-Verlag.

Byrnes, C. I., Gusev, S. V., & Lindquist, A. (1999). A convex optimization approach to the rational covariance extension problem. *SIAM Journal on Control and Optimization, 37*, 211–229.

Calafiore, G., & Campi, M. C. (2005). Uncertain convex programs: Randomized solutions and confidence levels. *Mathematical Programming, 102*, 25–46.

Calafiore, G., & Campi, M. C. (2006). The scenario approach to robust control design. *IEEE Transactions on Automatic Control*, *51*(5), 742–753.

Campi, M. C., & Weyer, E. (2005). Guaranteed non-asymptotic confidence regions in system identification. *Automatica, 41*(10), 1751–1764.

Cao, C., & Annaswamy, A. M. (2003). Parameter convergence in nonlinearly parametrized systems. *IEEE Transactions on Automatic Control, 48*(3), 397–412.

Cassandras, C. G., & Lafortune, S. (1999). *Introduction to discrete event systems*. Kluwer Academic Publishers.

Cassandras, C. G., Pepyne, D. L., & Wardi, Y. (2001). Optimal control of a class of hybrid systems. *IEEE Transactions on Automatic Control, 46*(3), 398–415.

Cassandras, C. G., Wardi, Y., Melamed, B., Sun, G., & Panayiotou, C. G. (2002). Perturbation analysis for on-line control and optimization of stochastic fluid models. *IEEE Transactions on Automatic Control, 47*(8), 1234–1248.

Chiuso, A., & Picci, G. (2005). Consistency analysis of some closed-loop subspace identification methods. *Automatica, 41*(3), 377–391.

Del Moral, P. (2004). Genealogical and interacting particle approximations. *Springer Series: Probability and Applications, 37*, 1515–1528.

Doucet, A., & Wang, X. (2005). Monte Carlo methods for signal processing: A review in the statistical signal processing context. *IEEE Signal Processing Magazine, 22*(6), 152–170.

Elliott, R. E., Aggoun, L., & Moore, J. B. (1995). *Hidden Markov models: Estimation and control*. Springer-Verlag.

Gevers, M. (2000). Identification and validation for robust control. In P. Albertos, & A. Sala (Eds.), *Iterative identification and control* (pp. 185–208). Springer-Verlag.

Giridhar, A., & Kumar, P. R. (2006). Scheduling traffic on a network of roads. *IEEE Transactions on Vehicular Technology*, *50*, (to appear).

Glasserman, P., Heidelberger, P., Shahabuddin, P., & Zajic, T. (1999). Multilevel splitting for estimating rare event probabilities. *Operations Research, 47*, 585–600.

Goethals, I., Pelckmans, K., Suykens, J. A. K., & De Moor, B. (2005). Identification of MIMO Hammerstein models using least squares support vector machines. *Automatica, 41*(7), 1263–1272.

Hjalmarsson, H. (2005). From experiment design to closed-loop control. *Automatica, 41*(3), 393–438.

Jansson, H., & Hjalmarsson, H. (2005). Input design via LMIs admitting frequency-wise model specifications in confidence regions. *IEEE Transactions on Automatic Control, 50*(10), 1534–1549.

Jiang, S., Huang, Z., Chandra, V., & Kumar, R. (2001). A polynomial algorithm for testing diagnosability of discrete-event systems. *IEEE Transactions on Automatic Control, 46*(8), 1318–1321.

Johansson, K. H., Lygeros, J., Zhang, J., & Sastry, S. (2000). Hybrid automata: A formal paradigm for heterogeneous modeling. In *Proceedings of international symposium on computer-aided control system design* (pp. 123–128).

Kammer, L. C., Gorinevsky, D., & Dumont, G. A. (2003). Semi-intrusive multivariable model invalidation. *Automatica, 39*(8), 1461–1467.

Katayama, T. (2005). *Subspace methods for system identification*. Springer-Verlag.

Katayama, T., Kawauchi, H., & Picci, G. (2005). Subspace identification of closed loop systems by the orthogonal decomposition method. *Automatica, 41*(5), 863–872.

Krstic, M., & Wang, H. H. (2000). Stability of extremum seeking feedback for general dynamic systems. *Automatica, 36*(4), 595–601.

Lafortune, S., Teneketzis, D., Sampath, M., Sengupta, R., & Sinnamohideen, K. (2001). Failure diagnosis of dynamic systems: An approach based on discrete event systems. In *Proceedings of 2001 American control conference* (pp. 2058–2071).

Levine, W., & Hristu, D. (Eds.). (2005). *Handbook of networked and embedded control systems*. Birkhauser.

Ljung, L. (2001). Estimating linear time-invariant models of non-linear time-varying systems. *European Journal of Control, 7*, 203–219.

Mäkilä, P. M., & Partington, J. R. (2004). Least-squares LTI approximation of nonlinear systems and quasistationarity analysis. *Automatica, 40*(7), 1157–1169.

Mari, J., Stoica, P., & McKelvey, T. (2000). Vector ARMA estimation: A reliable subspace approach. *IEEE Transactions on Signal Processing, 48*(7), 2092–2104.

Miyasato, Y. (2000). A model reference adaptive controller for systems with uncertain relative degrees $r, r+1$ or $r+2$ and unknown signs of high-frequency gains. *Automatica, 36*(6), 889–896.

Nemeth, J. G., Kollar, I., & Schoukens, J. (2002). Identification of Volterra kernels using interpolation. *IEEE Transactions on Instrumentation and Measurement, 51*(4), 770–775.

Ninness, B., & Hjalmarsson, H. (2004). Variance error quantifications that are exact for finite-model order. *IEEE Transactions on Automatic Control, 49*(8), 1275–1291.

Park, S. J., & Lim, J. T. (2000). Robust and nonblocking supervisor for discrete-event systems with model uncertainty under partial observation. *IEEE Transactions on Automatic Control, 45*(12), 2393–2396.

Perez-Cruz, F., & Bousquet, O. (2004). Kernel methods and their potential use in signal processing. *IEEE Signal Processing Magazine, 21*(3), 57–65.

Qin, S. J., Lina, W., & Ljung, L. (2005). A novel subspace identification approach with enforced causal models. *Automatica, 41*(12), 2043–2053.

Roll, J., Nazin, A., & Ljung, L. (2005). Nonlinear system identification via direct weight optimization. *Automatica, 41*(3), 475–490.

Rotea, M. A. (2000). Analysis of multivariable extremum seeking algorithms. In *Proceedings of the American control conference*.

Rudie, K., & Willems, J. C. (1995). The computational complexity of decentralized discrete-event control problems. *IEEE Transactions on Automatic Control, 40*(7), 1313–1319.

Rudie, K., & Wonham, W. M. (1992). Think globally, act locally: Decentralized supervisory control. *IEEE Transactions on Automatic Control, AC-37*(11), 1692–1708.

Sampath, M., Sengupta, R., Lafortune, S., Sinnamohideen, K., & Teneketzis, D. C. (1996). Failure diagnosis using discrete-event models. *IEEE Transactions on Control Systems Technology, 4*(2), 105–124.

Sampath, M., Sengupta, R., Lafortune, S., Sinnamohideen, K., & Teneketzis, D. C. (2004). Hysdel—a tool for generating computational hybrid models for analysis and synthesis problems. *IEEE Transactions on Control Systems Technology, 12*(2), 235–249.

Schoukens, J., Pintelon, R., Dobrowiecki, T., & Rolain, Y. (2005). Identification of linear systems with nonlinear distortions. *Automatica, 41*(3), 491–504.

Sic, T. S., & Lafortune, S. (2005). Decentralized supervisory control with conditional decisions: Supervisor realization. *IEEE Transactions on Automatic Control, 50*(8), 1205–1211.

Silva, B. I., & Krogh, B. H. (2000). Formal verification of hybrid systems using checkmate: A case study. In *Proceedings of 2000 American control conference* (pp. 1679–1683).

Spall, J. C. (2003). Estimation via Markov Chain Monte Carlo. *IEEE Control Systems Magazine, 23*(2), 34–45.

Takai, S., & Ushio, T. (2003). Supervisor synthesis for a class of concurrent discrete event systems. In *Proceedings of 42nd IEEE conference on decision and control* (pp. 2686–2691).

Tempo, R., Calafiore, G., & Dabbene, F. (2005). *Randomized algorithms for analysis and control of uncertain systems*. Springer-Verlag.

Tomlin, C. J., Mitchell, I., Bayen, A. M., & Oishi, M. (2003). Computational techniques for the verification of hybrid systems. *Proceedings of the IEEE, 91*(7), 986–1001.

Vapnik, V. N. (1996). *Statistical learning theory.* Wiley.

Varaiya, P. (2005). Reducing highway congestion: An empirical approach, CDC 2005 Bode lecture. *European Journal of Control, 11*, 301–309.

Veres, S. M. (1999). Iterative identification and control redesign via unfalsified sets of models: A basic scheme. *International Journal of Control, 72*(10), 887–903.

Vidyasagar, M. (1997). *A theory of learning and generalization*. Springer-Verlag.

Vidyasagar, M. (2001). Randomized algorithms for robust controller synthesis using statistical learning theory. *Automatica, 37*(10), 1515–1528.

Yousef, N. R., & Sayed, A. H. (2001). A unified approach to the steady-state and tracking analyses of adaptive filters. *IEEE Transactions on Signal Processing, 49*(2), 314–324.

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