Modelling, Identification and Control

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Abstract. In this chapter we first review the changing role of the model in control system design over the last fifty years. We then focus on the development, over the last ten years, of the intense research activity and on the important progress that has taken place on the interplay between modelling, identification and robust control design. The major players of this interplay are presented; some key technical difficulties are highlighted, as well as the solutions that have been obtained to conquer them. We end the chapter by presenting the main insights that have been gained by a decade of research on this challenging topic.

1 A not so brief historical perspective

There are many ways of describing the evolution of a field of science and engineering over a period of half a century, and each such description is necessarily biased, oversimplified and sketchy. But I have always learned at least some new insight from such sketchy descriptions, whoever the author. Thus, let me attempt to start with my own modest perspective on the evolution of modelling, identification and control from the post-war period until the present day[1].

Until about 1960, most of control design was based on model-free methods. This was the golden era of Bode and Nyquist plots, of Ziegler-Nichols charts and lead/lag compensators, of root-locus techniques and other graphical design methods.

From model-free to model-based control design
The introduction of the parametric state-space models by Kalman in 1960, together with the solution of optimal control and optimal filtering problems in a Linear Quadratic Gaussian framework [26,27] gave birth to a tremendous development of model-based control design methods. Successful applications abounded, particularly in aerospace, where accurate models were readily available.

From modelling to identification
The year 1965 can be seen as the founding year for parametric identification with the publication of two milestone papers. The paper [23] sets the stage

[1] And by post-war I refer to the second world war, and not what the old folks call the 'Great War', as if a war could ever be great.

for state space realization theory which will, 25 years later, be the major stepping stone towards what is now called subspace identification. The paper [5] proposes a Maximum Likelihood framework for the identification of input-output (i.e. ARMAX) models that gave rise to the celebrated prediction error framework that has since proven so successful. Undoubtedly – and as is so often the case – the advent of identification theory was spurred by a desire to extend the applicability of model-based control design to broader and broader fields of applications, for which no reliable models could be obtained, at least at a reasonable cost.

From the elusive true system to an approximate model
Most of the early work on identification theory was directed at developing more and more sophisticated model sets and identification methods with the elusive goal of converging to the "true system", under the assumption that the true system was in the model set. It is not until the eighties that the effort shifted towards the goal of approximating the true system, and of characterizing this approximation in terms of bias and variance error on the identified models. Once it is recognized that the identified model is an approximates the true system with some error, it makes sense to tune the identification towards the objective for which the model is to be used. One of the main contributions of L. Ljung's book [30] was to introduce the engineering concept of *identification design*, and to lay down some foundations for the formal design of goal-oriented identification. However, the specific contributions to control-oriented identification design were virtually nonexistant until 1990.

From certainty equivalence to robust control design
A consequence of the early faith that the true system could be modelled almost perfectly and of the development of more and more sophisticated model-based control design methods was the application of the "certainty equivalence principle" for control design. Whether the model had been obtained by mathematical modelling or by identification from data, it was taken to represent the true system. It is as if the prevailing habits of adopting model-based control design techniques had almost completely obliterated our grandfathers' cautionary adoptions of gain and phase margins. There was an obvious need to introduce a formal way of injecting stability and performance safeguards in the model-based control design approaches. This is precisely what the robust control theory initiated in the eighties (see [40]) aimed at achieving: it was an attempt to preserve the obvious advantages of model-based control design while at the same time introducing robustness to model errors. Much of the effort in the development of robust control theory had to do with various ways of introducing model errors in the closed loop system configuration: descriptions of additive, multiplicative, feedback errors, coprime factor perturbations, linear factor transformations flourished.

From separate to synergistic design

It is not until the early nineties that the identification community and the robust control community became aware of each other's work. Much of the successful robust control applications had been performed in situations where modelling techniques were able to deliver a fairly accurate model on the basis of first principles, and where it was reasonable to assume a priori bounds on the noise and modelling errors. Process control applications, in which identification methods are often the only path to a reasonable model and where these methods have also achieved many of their successes, were for the most part outside this realm. As a result of the lack of communication between these two research communities, the model uncertainty descriptions on which robust control design methods had been based (frequency domain descriptions, essentially) were very inconsistent with the tools delivered by prediction error (PE) identification. As a matter of fact, PE identification had very little to offer in terms of explicit quantification of the error in an estimated transfer function. A fortiori, there was very little understanding of the interplay between the experimental conditions under which identification was performed and the adequacy of the resulting model (and model error) for control design. The prevailing philosophy was "First estimate the best possible model, then design the controller on the basis of this estimated model and – possibly – of an estimate of the model error." Since the main stumbling block in applying robust control design techniques from identified models was the unavailability of adequate uncertainty descriptions, much of the early effort at combining identification with robust control theory went in the development of novel identification techniques that would deliver the kind of frequency domain uncertainty descriptions that the robust control theory of the eighties required. The problem is that an identification method whose sole merit is to deliver an error bound may well produce a nominal model as well as an uncertainty set that are ill-suited for robust control design.

From model reduction to control-oriented low order models

Of course, there is no fundamental objection to first spending a significant amount of effort in obtaining a very accurate model (including a model uncertainty set) for the unknown system by modelling and/or identification techniques, and then computing a robust controller from this model and its uncertainty set. This would typically lead to a high order controller, which can of course later be reduced. However, there are both practical and theoretical reasons for adopting an identification method that directly leads to a low order model and an uncertainty set that are tuned for robust control design. This will be one of the central themes of the present book.

A practical motivation is that there is no reason to waste enormous modelling and/or identification efforts at obtaining a highly accurate and complex model with fairly accurate error bounds if a simple model is obtained with much less effort and leads to a controller that achieves similar performance with the same stability safeguards. Examples abound to illustrate that extremely simple controllers, obtained from extremely simple models, often achieve high performance on complex systems. One such example will be presented for motivation in Subsection 3. A theoretical motivation is that, as shown recently [25], a low order model for control design, obtained by model reduction techniques from a high order model, will have higher variance error than a low order model that has been identified directly for the purpose of control design.

Thus, much of the research effort of the nineties has focused on establishing synergies between identification and robust control design methods. These efforts have been directed at better matching the technical tools of both theories: new identification techniques have been developed that produced the kind of frequency domain model uncertainty descriptions that are prevalent in mainstream robust control theory, while new robust control analysis and design tools have been developed that are consistent with the parametric descriptions delivered by mainstream PE identification theory. More importantly perhaps, important progress has been made at producing robust identification and control design procedures in which the experimental conditions and the identification criterion are designed to match the control performance criterion. Such matching must be achieved not only for the low order nominal model (this is a design problem for the bias error distribution), but also for the model uncertainty set (this is a design problem for the variance error distribution). The bias and variance error are affected by different aspects of the experimental conditions and of the identification criterion.

From adaptive control to iterative control design

Dual control and adaptive control were two early attempts to address the issue of parametric uncertainty and model-based control design in a synergistic way. In dual control the parameter estimation and the control design mechanism are obtained jointly as the result of a single but very complex optimization problem. In adaptive control, the parameter adjustment scheme is subsidiary to the control objective. Both schemes were essentially developed for the case where the structure of the true system is known, and where the system is in the model set. The solution of the dual control problem proved to be computationally intractable, even in the simplest cases. As for adaptive control, after convergent mechanisms had been devised for the ideal case where the system is in the model set, attempts were made to robustify the adaptive control algorithms in order to take account of some modest degree of uncertainty. These attempts essentially consisted of introducing cautionary safeguards in the computation of the gain of the parameter adjustment scheme; see e.g. [1] for a representative example of these efforts. The major difficulty with adaptive control schemes is that the parameters of the feedback control system change at every sampling instant, making the closed-loop dynamics nonlinear and the stability analysis of these dynamics extremely complex.

The study of the interplay between identification and control design, undertaken by various groups around 1990, led to the formulation of identification criteria that were a function of the underlying control performance criteria. As with all optimal experiment design results, the optimal solution is a function of the unknown system, and the only practical way to approach this optimal solution is then to attempt an iterative design. This was pointed out by various authors (see e.g. [32] and will be illustrated later in this chapter. In identification for control, this means that a succession of model updates and controller updates are intertwined. Each new model is identified from data obtained on the real plant on which the most recent controller is acting; each new controller is in turn computed from this most recent model. Representative examples of such iterative schemes, which first emerged in the early nineties, can be found in [35,29,41].

A major difference between the iterative identification and control design schemes of the nineties and the earlier adaptive control schemes is that in the former the model and controller are kept constant in between two model and/or controller iterations. Thus, the closed loop system performs in a batch-like mode, in which stationarity can be assumed – and hence asymptotic analysis can be applied – during the collection of each batch of data. This removes one of the fundamental problems of adaptive control schemes, namely the transient instability problem: see [3]. Nevertheless, it was shown in [22] that, even with the simplest control performance criterion, such iterative schemes are not guaranteed to converge to a minimum of the control performance criterion over all models in the chosen restricted complexity model set. This may cause the iterative parameter adjustment scheme to drift to a controller parameter vector that makes the closed loop system unstable.

As a result, important work has been undertaken to introduce prior stability checks into the iterative identification and control schemes. This work, which is still underway, has led to the inclusion of caution in the controller adjustment so that, from a presently operating stabilizing controller and an updated model, stability and/or performance improvement guarantees can be established for the next controller [11,2].

In the work on iterative identification and control design, the focus has been first on the formulation of control-oriented identification criteria, i.e. the successive identification criteria are a function of the control performance criteria. As a result, the succession of nominal models have a bias error distribution that are “tuned for control design”. This means that the (typically low order) nominal models have a bias error that is small in the frequency areas where it needs to be small for the design of a better controller, typicaly around the present cross-over frequency. Recent work has focused on the design of a control-oriented distribution of the variance error of the identified models, again leading to iterative designs [16,9]. The idea is that, since one can manipulate the shape of the model uncertainty set by the choice of the experimental conditions under which the new model is identified, one should attempt to obtain model uncertainty sets for which the class of controllers achieving stability and the required performance with all models of that set is as large as possible.

2 A typical scenario and its major players

During the extensive research of the last decade on the interplay between identification and robust control, important progress has been made and some key lessons have been learned. In this section we illustrate some of the salient features of the interplay. First, we present the typical scenario to which iterative identification and control design schemes are usually applied, as well as the major players.

In many applications the system to be controlled is very complex and possibly nonlinear, and it would therefore require a complex dynamical model to represent it with high fidelity. Any model-based control design procedure would therefore lead to a complex or high order controller, since the complexity of a model-based controller is of the same order as that of the system. The practical situation, considered here, is where we want the to-be-designed controller to be linear and of low order.

Since we want to focus on ideas and concepts, rather than on technically complicated issues, and for the sake of simplicity, we shall assume that the unknown true system can be represented with high fidelity by a single-input single-output linear time-invariant system. Thus, we assume that there is an unknown "true system" represented by

$$\mathcal{S} : y_t = G_0(z)u_t + v_t, \tag{1}$$

where $G_0(z)$ is a linear time-invariant causal operator, y is the measured output, u is the control input, and v is noise, assumed to be quasistationary.

A typical situation is that we can perform experiments on this system with the purpose of designing a feedback controller. Most often, the system is already under feedback control, and the task is to replace the present controller by one that achieves better performance. This situation is representative of very many practical industrial situations. We denote the present controller by C_{id}:

$$u_t = C_{id}(z)[r_t - y_t], \tag{2}$$

where r_t is the reference excitation.

Using any set of N data collected on the unknown system, in open loop or in closed loop, we can apply Prediction Error (PE) identification and compute a model G_{mod} of the unknown G_0.[2] The model G_{mod} is typically

[2] One would also compute a noise model for $v(t)$ in the form $v(t) = H_{mod}(z)e(t)$, with $e(t)$ white noise, but to keep things simple we shall only discuss here the interplay between the input-output model and the controller.

a low order approximation of the unknown G_0. Various validation methods have also been developed for the estimation of an uncertainty set $\mathcal{D}$ around G_{mod}, with the property that $G_0 \in \mathcal{D}$ with probability α, where α is any desired level close to 1 (e.g. $\alpha = 0.95$): see e.g. [18,19,8].

The traditional scenario in model-based robust control design was: *Using the model G_{mod} and the uncertainty set $\mathcal{D}$ (if available), design a new controller $C(z)$ that achieves closed loop stability and meets the required performance with all models in $\mathcal{D}$, and hence with the unknown true system G_0.* For this scenario to be successful, a very accurate model G_{mod} was typically required.

The present scenario based on the new insights gained on the interplay between identification and robust control is: *On the basis of the required performance, of any knowledge of the unknown system, and of the performance achieved with the present controller (if any), design a control-oriented identification experiment that produces a (new) G_{mod} and a (new) uncertainty set $\mathcal{D}$; then design a new controller $C(z)$ that achieves closed loop stability and meets the required performance with all models in $\mathcal{D}$, and hence with the unknown true system G_0.* If necessary, repeat this design procedure, possibly with a more demanding performance criterion. In most versions of this new scenario, one first computes a class of controllers $\mathcal{C}(G_{mod}, \mathcal{D})$ which all achieve the required performance with all models in $\mathcal{D}$; the new controller C is then chosen within this class in such a way as to have some additional nice features (e.g. low complexity).

The goal of the new scenario is to achieve the same or better performance based on models of lower complexity. In addition, the class of controllers $\mathcal{C}$ that achieve the required performance is larger because the model uncertainty set $\mathcal{D}$ is tuned towards that aim. All in all, the same or better performance is achieved with a controller that is easier to compute and of lower complexity than is possible with the traditional scenario.

The players within this (iterative) identification and robust control design scenario are therefore:

- the unknown plant G_0
- the present controller C_{id} (if any)
- the present model G_{init} (if any)
- the identified model G_{mod}
- the uncertainty set of models $\mathcal{D}$ around G_{mod}
- the controller set $\mathcal{C}$ of controllers that achieve the prescribed performance
- the new controller $C \in \mathcal{C}$

Except for the unknown plant, the identification and control designer has some handle on all other players. It is the complexity of the interplay between all these players that makes the problem so challenging and interesting. A lot of progress has been accomplished and a lot of new insights gained, but it is no wonder that it has taken a decade so far to understand and conquer all the stumbling blocks along the way.

3 Some important new insights

The study of the interplay between the different actors has led to some important new insights, and to significant progress on some key technical issues.

High performance control with low order models
Experience shows that simple models often lead to high performance controllers on complex processes. To illustrate this point, let us mention the modeling, identification and control application of the Philips Compact Disc (CD) Player, taken from [12].

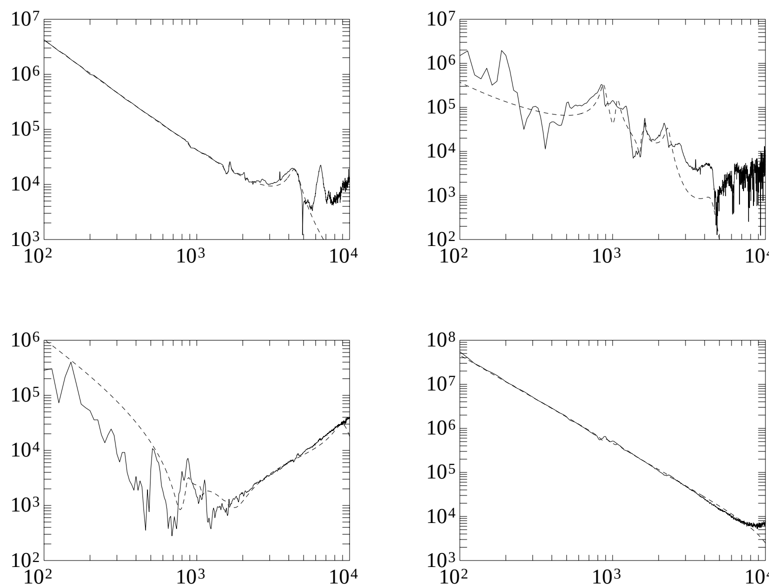


Fig. 1. Amplitude of spectral estimate (—) and of parametric model (- -)

Following the track on a CD involves two control loops. A first permanent magnet/coil system mounted on the radial arm positions the laser spot in the direction orthogonal to the track. A second permanent magnet/coil system controls an objective lens which focuses the laser spot on the disc. The control system therefore consists of a 2-input/2-output system, with the spot position errors (in both radial and focus directions) as the variables to be controlled, and the currents applied to the magnet/coil actuators as the control variables. The modeling of this system using finite element methods or its estimation using spectral analysis techniques would lead to a 2-input/2-output model whose McMillan degree would be of the order of 150. However, by using an identification for control design criterion, a 16-th order model has been identified that leads to excellent control performance: see [12] for details. A comparison between the spectral estimates and the identified models for the 4 input-output channels is presented in Figure 1. The spectral estimates have been obtained by taking 100 averages over 409,600 time samples. The parametric models have been identified using 2,000 closed loop data samples.

A controller of degree 150, say, based on the full-order model obtained by modelling techniques, would be practically useless. Instead, data-based control-oriented identification led to an approximate (and simplified) model, and to a reduced order controller that gave high performance.

The role of changing experimental conditions

It is now well recognized that one can find two plants whose Nyquist diagrams are practically indistinguishable, and a controller for the two plants for which the two closed-loop behaviours are enormously different. Thus the quality of a plant model, in a closed-loop setting, can only be assessed in conjunction with the controller with which it must operate. This was beautifully pointed out in [36], where the following two principles were laid out.

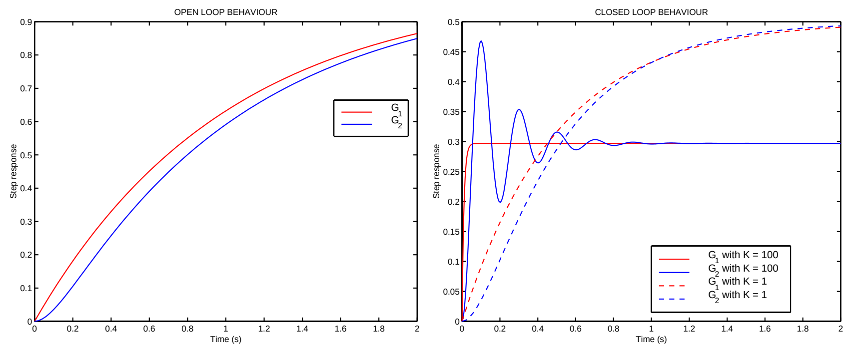
Modelling Principle 1: arbitrarily small modelling errors can lead to arbitrarily bad closed-loop performance. The higher the performance sought of the controller, the more readily this phenomenon occurs. We illustrate this with the following example. Consider the two transfer functions

$$G_1(s) = \frac{1}{s+1} \quad \text{and} \quad G_2(s) = \frac{1}{(s+1)(0.1s+1)} \tag{3}$$

The left hand side of Figure 2 compares their open loop step responses, while the right hand side compares the closed loop step responses with a proportional feeback controller, for two different values of the constant gain: $C = 1$ and $C = 100$.

Modelling Principle 2: larger open loop modelling errors do not necessarily lead to larger closed-loop modelling errors. Or stated otherwise, a very poor open loop model may yield excellent matching in closed loop. To illustrate this, we take the same plant $G_1(s)$ as above, and we now consider the model $G_2(s) = \frac{1}{s}$. Figure 3 illustrates that, even though G_2 would be rejected by any engineer as a model for G_1, the behaviours of the plants G_1 and G_2, in closed loop with a proportional controller of gain $C = 100$ are almost indistinguishable.

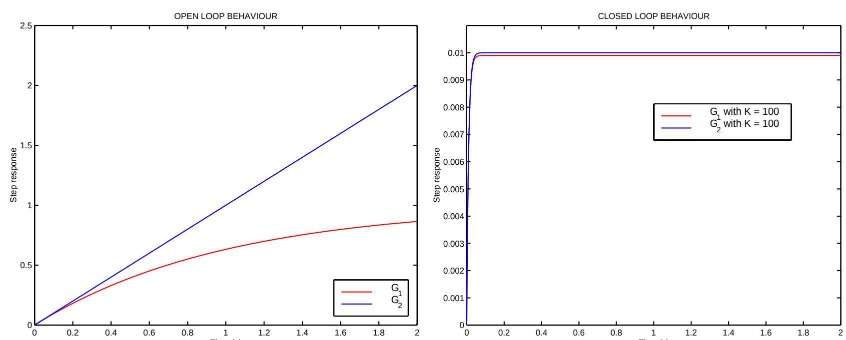
The issue is that models, and the task of finding them (by modelling or identification), can only have their quality evaluated for a particular set of experimental conditions. Changing from open-loop operation to closed-loop operation with a specific controller is an obvious change of experimental conditions; but so is any change of a controller.



Open loop

Closed-loop
C=100(full)/C=1(dashed)

Fig. 2. Open loop (left) and closed loop (right) step responses of G_1 and G_2 with two different controllers



Open loop

Closed-loop with C=100

Fig. 3. Open loop (left) and closed loop (right) step responses of G_1 and G_2 with two different controllers

The need for iterative identification and control design

To illustrate the need for iterative design, we take the simplest possible control design objective: model reference control. Thus, consider the true system (1) and suppose we have identified a model $\hat{G}(z) = G(z, \hat{\theta})$ of G_0 from some parametrized set of low order models $\{G(z, \theta)\}$. Consider a control law

$$u_t = C(z)[r_t - y_t], \tag{4}$$

and assume that our control design objective is to design $C(z)$ such that the closed loop transfer function from v_t to y_t is some prespecified $S(z)$. Then, given a model $\hat{G}(z)$, the controller $C(z)$ is computed from[3]

$$\frac{1}{1+\hat{G}(z)C(z)} = S(z). \tag{5}$$

Compare the real closed loop system of Figure 4 with the designed closed loop system of Figure 5, with both loops driven by the same reference signal r_t.

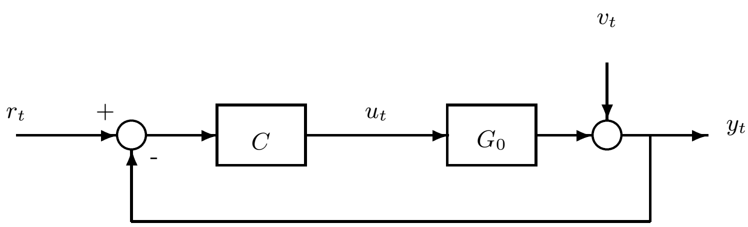


Fig. 4. Actual closed loop system

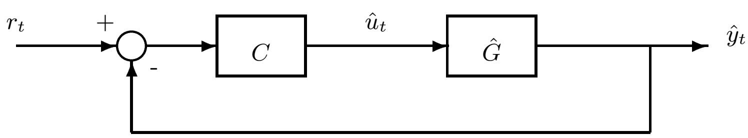


Fig. 5. Designed (or nominal) closed loop system

Now, staring at Figures 4 and 5, one observes that:

$$y_t = \frac{G_0 C}{1+G_0 C} r_t + \frac{1}{1+G_0 C} v_t, \qquad u_t = \frac{C}{1+G_0 C} r_t - \frac{C}{1+G_0 C} v_t,$$
$$\hat{y}_t = \frac{\hat{G}C}{1+\hat{G}C} r_t. \tag{6}$$

The 'control performance error' is defined as the error between the actual and the designed outputs:

$$y_t - \hat{y}_t = \left[\frac{G_0 C}{1+G_0 C} - \frac{\hat{G}C}{1+\hat{G}C} \right] r_t + \frac{1}{1+G_0 C} v_t \tag{7}$$

As observed in [4], this error can be rewritten as

$$y_t - \hat{y}_t = S(z)[y_t - G(z,\hat{\theta})u_t]. \tag{8}$$

[3] We assume for simplicity here that a causal solution exists for $C(z)$, since this is not the focal point of our discussion.

Equation (8) can be seen as an equality between a control performance error on the left hand side (LHS) and a filtered identification prediction error (for an output error model) on the right hand side (RHS). Thus, it appears that if θ is obtained by minimizing the Mean Square of the RHS of (8), i.e. by closed loop identification with a filter $S(z)$, then this will minimize the Mean Square control performance error. In other words, apparently there is a perfect match between control error and identification error. However, the controller $C(z)$ is also a function of the model parameter vector θ via (5). Since the data collected on the real closed loop system of Figure 4 are a function of $C(z)$, they are also dependent on θ. Hence, a more suggestive and correct way to write (8) is as follows:

$$y_t - \hat{y}_t = S(z)[y_t(\theta) - G(z,\theta)u_t(\theta)]. \tag{9}$$

Even though the RHS of (9) looks like a closed loop prediction error, it cannot be minimized by standard identification techniques, because θ appears everywhere and not just in $G(z,\theta)$.

As a consequence, the approach suggested in most 'identification for control' schemes is to perform identification and control design steps in an iterative way, whereby the i-th identification step is performed on filtered closed loop data collected on the actual closed loop system with the $(i-1)$-th controller operating in the loop, i.e.

$$y_t - \hat{y}_t = S(z,\hat{\theta}_{i-1})[y_t(\hat{\theta}_{i-1}) - G(z,\theta)u_t(\hat{\theta}_{i-1})]. \tag{10}$$

Although other variants exist, a typical iterative scenario is therefore as follows:

$$\hat{G}_1 \rightarrow C_1 \rightarrow \hat{G}_2 \rightarrow C_2 \rightarrow \ldots \rightarrow \hat{G}_i \rightarrow C_i \rightarrow \hat{G}_{i+1} \rightarrow C_{i+1} \rightarrow \ldots$$

We refer the reader to [15], [7] and [38] for details and for a survey on such iterative schemes.

An interesting question is whether by iteratively minimizing over θ the mean square of the prediction errors defined by (10), one will converge to the minimum of

$$J(\theta) \stackrel{\triangle}{=} E\{S(z,\theta)[y_t(\theta) - G(z,\theta)u_t(\theta)]\}^2. \tag{11}$$

This question was analyzed in [22], where it was shown that the iterative identification and control schemes do not generically converge to the achievable minimum (within the model/controller set) of the control performance cost.

Despite this disappointing news from a theoretical point of view, the concept of iterative identification and control design was rapidly adopted in applications, in particular in process control applications. Representative examples can be found in [31,34,12,24,10]. One reason is that it is typical in such applications that large numbers of closed loop data are flowing into the control computer, and it then makes a lot of sense to use these data to replace the existing controller by one that achieves better performance. The practical impact of iterative closed loop identification and controller redesign has been assessed in [28], where some interesting observations are made on the distinction between this batch-like mode of operation and the more classical theory and methods of adaptive control.

The need for cautious adjustments

As a result of the absence of convergence guarantees of the iterative schemes to a minimum of the control performance criterion, the procedure may well converge to a controller that makes the actual closed-loop system unstable. In addition, even in a situation where the procedure does converge to a minimum of the cost criterion, nothing guarantees that along the way the controller parameter vector will not take a transient value that destabilizes the true system. In order to circumvent these difficulties, a lot of work has been devoted to the search for prior stability guarantees that can be checked before the new controller is implemented. The generic situation is as follows.

At some stage of the iterations a controller C_i, that was computed from a model $\hat{G}_i$, is operating on the true system G_0. This controller stabilizes G_0 and achieves with G_0 a performance $J(G_0, C_i)$. With data collected on the closed loop system (G_0, C), a new model $\hat{G}_{i+1}$ is identified, from which a new controller C_{i+1} is computed, which has a nominal performance $J(\hat{G}_{i+1}, C_{i+1})$. Before the new controller is actually applied to the plant G_0, one would like to have some prior guarantee that this new controller will stabilize and achieve a better performance with G_0. In the last few years a significant amount of work has addressed this problem, either from a robust stability point of view, or from a robust performance point of view. Most of these results have led to the need to introduce some "caution" in the iterations, in that some measure of distance between the present and the new controller must be kept small. The origin of this need for caution is to be found in the observations made above about *the role of the changing experimental conditions.* As for the technical nature of these results, let it suffice here to say that the bound on the admissible change between two successive controllers is related to the distances between the successive closed loop systems, and to their corresponding performances. For details, see later chapters in this book or e.g. [33,11,2,6].

The benefits of closed-loop identification

One of the important lessons that has emerged from the study of the interplay between identification and control is the benefit of closed-loop identification when the model is to be used for control design. Until the late eighties, it was commonly accepted within the identification community that closed-loop identification was preferably to be avoided. Optimality of closed loop identification was first shown in the ideal context of optimal experiment design with full order models (i.e. where variance errors only are considered) [17,21,14], at least when the optimal controller contains a noise rejection objective . In the more practical case of identification with reduced order models, it is the required connection between the control performance criterion (obviously a closed-loop criterion) and the identification criterion, as describes above, that establishes the need for closed-loop identification.

This observation triggered an important new activity in the design of special purpose closed-loop identification methods, the main goal pursued by these new methods being to obtain a better handle on the bias error in closed-loop identification [20,37,39,13]. From a practical point of view, the newly discovered benefits of closed-loop identification methods and the development of some of these special purpose methods came as welcome news to process control engineers who had never really liked the idea of opening the loop and applying special test signals to their systems in order to identify them.

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