Plug & Play Control: Control Technology towards new Challenges

Jakob Stoustrup*

Automation & Control, Department of Electronic Systems, Aalborg University, Fr. Bajers Vej 7C, DK-9220 Aalborg, Denmark

Control engineering is in many ways a mature technology that has found its way into almost every industrial sector with an almost countless number of successful applications. Nevertheless, there still remains significant challenges to overcome that prevent the technology from further spread.

One of these challenges is related to the fact that large industrial processes are always live *systems in the sense that they are subject to constant change in terms of instrumentation (sensors and actuators) and in terms of subsystems that are added or removed. This means that an advanced control system might be based on a system model that is valid only for a rather short time span and might be turned off by the operator, when it seizes to operate satisfactorily for this reason. Moreover, most of the advanced design methodologies offered by our community are monolithic in nature, in the sense that the only way to modify the control system is to perform a completely new design of the whole system in response to what might be even tiny changes in instrumentation. Such a constant redesign of the whole control system is usually not feasible due to cost and commissioning issues.*

This paper is a position paper in the sense that it probably provides more questions than answers. The objective of the paper is to highlight some of the challenges that the control community is facing, if the advanced methods should be made applicable to a wider range of applications, in particular those that can be described as live systems for which sensors and actuators are added or removed, and likewise, for which subsystems are added or removed from time to time.

The challenge is defined as creating control systems that can automatically accommodate changes of this radical nature.

A number of industrial case studies to exemplify the challenges are described.

1. Introduction

Control engineering is becoming a very mature research area, and the literature is rich in algorithms to design control systems for even highly complex industrial systems. In industrial practice, however, several obstacles persist, which block the further spread of advanced control algorithms to complex industrial applications. One of these obstacles is related to the fact that large-scale industrial processes are live systems, which frequently are maintained and modified. This constitutes a major challenge to a majority of control design algorithms, which are 'monolithic' design procedures where a plant-wide controller is designed in a few steps. This means, that in principle even a minor change such as adding a sensor in principle would require a complete new design of the whole control system. This is often not acceptable due to the cost associated with advanced control design projects e.g. in terms of engineering/consultancy costs, insurance, and process down-time during installation.

If we specialize the problems outlined above to the special case of components that fail, a considerable

Correspondence to: J. Stoustrup; E-mail: jakob@es.aau.dk;

amount of previous work has been carried out in the areas of fault tolerant control and reconfigurable control, see e.g. [11, 31, 45, 47]. The work in this area, however, is mainly limited to handling a number of prespecified faults. The problem, e.g., of handling new components that are introduced is usually not addressed.

Another area that considers changing systems is the adaptive control area, see e.g. [5, 6]. In this line of research algorithms are suggested that allow controllers to track changes that can be described as changing parameters of the controlled system. This can to some extent capture subsystems that are replaced, if this does not involve new dynamics to be introduced. However, this theory has not been developed in order to incorporate e.g. new sensors or actuators that are introduced. Moreover, a majority of the control schemes that are proposed in this framework are of a monolithic nature.

In order to meet running structural changes of live systems by incremental changes of the control system, the control system has to have a hierarchical structure. Such structures have been studied in the areas of _decentralized control_, _distributed control_ and _hierarchical control_, see e.g. [40] and references therein. Recently there has been a renewed interest in this area from the perspective of _networked control systems_, see e.g. [33]. Although the control of systems that are subject to structural changes as outlined above has not been addressed in this line of work, the results obtained have a significant potential for providing the background for this type of problem.

Handling structural changes of course also involves handling the transients involved in the transfer from one configuration to another. The considerations required can be inspired from the literature on bumpless transfer, see e.g. the seminal papers [43, 44].

In this paper, we shall present a novel control concept, _plug & play control_, where we formulate a number of problems and a few solutions which meet the industrial need for control systems that can automatically reconfigure whenever a new component (e.g. an actuator, a sensor) is added or removed.

The paper presents an outline scheme for addressing problems of this type. The scheme proceeds in two parallel tracks by considering two classes of problems. In the first class of problems, the change to the system is considered to be known and related to a given model, describing the system and the original controller hierarchy. Therefore, the challenge is to identify where in the hierarchy it is required/beneficial to modify one or several controllers, taking into account the cost associated to such a change. In the second class of problems, it is not assumed that the

location of the new component is known to the design algorithm. Therefore, the first step will be to identify this, a notion referred to as _awareness_. The algorithms for establishing awareness are based on signal processing and system identification. Typically, the awareness of a new component is established gradually. Thus, the design algorithms for the new control loops associated with the new component will also have to be implemented in a gradual fashion.

2. The Plug & Play Control Challenge: Examples

The challenge portrayed in this paper is probably best illustrated by the virtue of typical examples. The following three examples are all real life case studies that have been proposed by the industrial partners in the research project [32].

1. A ventilation system for an animal stable is considered. The challenge is to allow the farmer to introduce new sensors in response to an unsatisfactory indoor climate in the stable, manifest e.g. by unnatural animal behavior. As the farmer anchors a new wireless temperature sensor somewhere in the wall, the challenge for the system is to identify the position of this new sensor and introduce a new control loop around it, such that the temperature it measures is stabilized at the right value. Thus, in this case study, the awareness algorithms are exploited and the control algorithms are implemented in a gradual fashion.
2. A district heating system is considered where a new pump station is introduced in order to supply hot water to a new apartment block. Topologically, the controllers of the new pumps operate in parallel with the existing controllers from a pressure point of view. Therefore, the system might become unstable, if attention is not paid. Since it is required by infrastructure concerns that the pump actions are based on decentral information only, the existing pumps have to become aware of the new station and adjust their controller gains and setpoints. It is demonstrated how the combined control system eventually converges to a state where the performance is close to that of a centrally designed controller.
3. A supermarket refrigeration system is considered where a new display case is introduced. Since the new display case share the same suction pressure as the existing ones, there is a strong system level coupling, which usually requires a re-design of several controllers in order to guarantee stability

and performance optimality. Based on a hierarchical model of the control system with compressor controllers, main valve controllers, fan controllers in the condensator and local display case temperature controllers, it is demonstrated that the algorithms are able to perform the right decision on which controllers to modify and how to modify them.

3. From Monolithic Control Design Towards Plug & Play Control Design

In this section, a research program in several parts is proposed in order to meet the vision described in Section 2. This research program consists of the following individual research tasks:

1. Describing service quality levels for networks and new protocols that allow automatic introduction of new components
2. Developing *awareness* algorithms
3. Developing self-configuring high-performance control laws based on awareness measures
4. Developing model based self-configuring high-performance control laws
5. Developing algoritms for determining survivability and performability measures
6. Developing design methods for self-configuring systems equipped with event based sensors and actuators

These research tasks will be described in the sequel.

The bottom layer prerequisite for achieving the research goal of plug & play control systems, i.e. control systems that automatically re-configure when a new sensor or actuator is added, is a communication system which facilitates plug & play at the hardware level. When e.g. a new sensor is plugged in, this sensor should be prompted for its type and parameters, which should be communicated to the control system. Thus, the first research task should be dedicated to *service quality levels for networks and protocols*, which will enable this functionality.

Once a new sensor has been introduced, the system should figure out how this component can be utilized to improve the process control. If the system does not have precise information on which process variable is measured by the sensor, the link between measurements and control objectives must be established empirically. Initially, such empirical information will be uncertain, but as large amounts of data has been processed, the measurements of the new sensor can be utilized with increasing confidence. This can be seen as an increasing *awareness* of the new sensor at system level. Thus, the second research task that has to be carried out is to develop algorithms for sensor and actuator awareness.

As the awareness of a new sensor increases, the information of the sensor should be fused with information from other sensors, and the fused information should be used for improving the control of the process. This is a highly non-trivial task, especially in cases, where a good model of the process cannot be assumed to pre-exist. Thus, the third research task to be carried out is to establish algorithms for *self-configuring high-performance control laws*, which should be developed based on awareness measures for the process in the face of little a priori knowledge.

For some industrial processes, however, a good model is available. If so, such a model should of course be exploited. Consequently, in the next research task, the *model-based* counterpart to the previous research task should be carried out, i.e., algorithms for exploiting new sensors or actuators in order to improve the overall performance are developed, based on mathematical models of the process.

The algorithms resulting from the two previously described research tasks in principle allows an engineer/designer of a process to move actuators and sensors around from socket to socket without limitation. In practice, however, only certain configurations are admissible. In order to operate the process safely at all, a certain minimal set of sensors and actuators are required. Such a set will be called a *survivability* set. However, in order to achieve proper performance, a larger set is required. Such a set is called a *performability* set. In consequence, the aim of the fifth research task should be to generate algoritms for determining survivability and performability measures in order to assist the operator to configure the process at hardware level.

Finally, as the results of the first research task (and similar attempts) become spread in industry, one should expect to see sensors and actuators, that are not sampled at a constant rate, but rather *event based* devices. Consequently, the sixth research task should address the design of self-configuring systems equipped with event based sensors and actuators.

4. Indicative Results

In the following subsections, we shall give a couple of results that were obtained in the project ([32]). It should be emphasized that these results are very premature, and far from constituting a realistic design paradigm that fulfills the agenda outlined above.

4.1. Closed-loop System Identification with New Sensors

The results in this subsection is largely based on the paper [10].

4.1.1. Introduction

The life-time of a controller for an embedded control system might be just as long as the life-time of the embedded system itself, especially if the control system has been designed to handle aging components (e.g. by adaptive control methods, see for instance [20] and/or faulty components (e.g. by fault tolerant control methods, see for instance [11], [12]).

In contrast, the life-time of a high level control system for a complex, industrial process is typically very short, as industrial control processes are often characterized by constant, structural modifications.

The short life-time of high level process control systems is often a limiting factor for companies, when they have to decide whether to invest in advanced control design projects. Obviously, the payback time has to be shorter than the controller life-time, but this precondition might not be satisfied for complicated processes that are subject to frequent, structural changes.

Furthermore, general technological progress may make new sensor and/or actuator hardware cheaper and more attractive than at the time of the original design, and restructuring (adding) the hardware in the loop may yield performance improvements that were deemed infeasible or too expensive at design time.

The problem here is that a vast majority of control design methodologies are *monolithic* in the sense that they embark from a model of an uncontrolled (open-loop) system and outputs a full, multivariable control system, which does not exploit any knowledge or functionality from previous designs. On the other hand, when new sensor and/or actuator hardware becomes available for use in a control system, it is often desirable to retain the existing control laws and apply the new control capabilities in a gradual online fashion rather than decommissioning the entire existing control system and replacing it with the new system, see for example [22, 25, 28, 38].

In order to utilise the new hardware, some sort of system identification will typically be required in order to design controllers with good stability and performance properties. Furthermore, since large-scale plants are typically not permitted to operate in open loop – the plant might for instance not operate acceptably without a controller forcing it to stay within the relevant operating range – *closed-loop* identification of the plant is usually necessary. How-ever, closed-loop identification tends to be much more difficult than open-loop identification. It will therefore be convenient to adopt the system identification to the control strategy in some way, preferably even to the point of obtaining 'open-loop-like' qualities. The so-called *Hansen scheme* [4, 16, 18, 26, 37] employs the *Dual Youla-Kucera* parameterisation [24], [42] of all linear plants stabilised by a given controller to transform the closed-loop identification problem into an open-loop-like problem. See also [3] and the references therein.

In this subsection, we show how the Hansen scheme can be reformulated to deal with new measurements that become available during online operation. The original plant is embedded in a larger system, in which hitherto unobservable dynamics is revealed by letting a new sensor come online. We show how the identification of the newly revealed dynamics is equivalent to the identification of a surprisingly simple dual Youla-Kucera parameter.

The outline of the rest of this subsection is as follows. Subsection 4.1.2 first provides an overview of the Youla-Kucera parameterisation and the Hansen-scheme closed-loop system identification framework. Subsection 4.1.5 then presents the main contribution of this work, an extension of the Hansen scheme to accommodate new sensor measurements. Subsection 4.1.6 then illustrates the usefulness of the scheme, and finally Subsection 4.1.7 sums up the conclusions of the work.

4.1.2. Dual Youla-Kucera Parameterisation

In this subsection we provide some preliminaries, which will be employed in the subsequent Subsection 4.1.5. All results in this subsection are equally valid in continuous and discrete time. Our notation is standard, as established in e.g., [46].

4.1.3. Basic Parameterisation

Consider a LTI system G mapping a set of inputs to a set of outputs:

$$y = Gu \tag{1}$$

where $y \in \mathbb{R}^p$ is the measurement vector and $u \in \mathbb{R}^m$ is the input vector. If G is stabilisable and detectable, it can be stabilised by some appropriate feedback controller, for instance an observer-based controller (see e.g. [46]).

Any proper G can be written as a right, respectively left, coprime factorisation of the form:

$$G = NM^{-1} = \tilde{M}^{-1}\tilde{N} \tag{2}$$

with $N, M, \tilde{M}, \tilde{N} \in \mathcal{RH}_\infty$. Correspondingly, a controller K that stabilises G can be factorised as

$$K = UV^{-1} = \tilde{V}^{-1}\tilde{U} \tag{3}$$

where $U, V, \tilde{U}, \tilde{V} \in \mathcal{RH}_\infty$. These coprime factorisations can be chosen to satisfy the double *Bezout identity*

$$\begin{bmatrix} \tilde{V} & -\tilde{U} \\ -\tilde{N} & \tilde{M} \end{bmatrix} \begin{bmatrix} M & U \\ N & V \end{bmatrix} = \begin{bmatrix} M & U \\ N & V \end{bmatrix} \begin{bmatrix} \tilde{V} & -\tilde{U} \\ -\tilde{N} & \tilde{M} \end{bmatrix} = \begin{bmatrix} I & 0 \\ 0 & I \end{bmatrix} \tag{4}$$

For example, if G has the state space realisation

$$G = \left[\begin{array}{c|c} A & B \\ \hline C & D \end{array}\right] \tag{5}$$

with $A \in \mathbb{R}^{n \times n}, B \in \mathbb{R}^{n \times m}, C \in \mathbb{R}^{p \times n}$ and $D \in \mathbb{R}^{p \times m}$ being constant matrices and K an observer-based feedback controller of the form

$$K = \left[\begin{array}{c|c} A + BF + LC + LDF & -L \\ \hline F & 0 \end{array}\right] \tag{6}$$

with $F \in \mathbb{R}^{m \times n}$ and $L \in \mathbb{R}^{n \times p}$ chosen such that the matrices $A + LC$ and $A + BF$ are stable, the double Bezout identity is satisfied by choosing the factorisation

$$\begin{bmatrix} M & U \\ N & V \end{bmatrix} = \left[\begin{array}{c|cc} A + BF & B & -L \\ \hline F & I & 0 \\ C + DF & D & I \end{array}\right] \tag{7}$$

$$\begin{bmatrix} \tilde{V} & -\tilde{U} \\ -\tilde{N} & \tilde{M} \end{bmatrix} = \left[\begin{array}{c|cc} A + LC & -(B + LD) & L \\ \hline F & I & 0 \\ C & -D & I \end{array}\right] \tag{8}$$

All stabilising controllers for some fixed system G based on some stabilising K factorised as in (3) can now be written according to the Youla-Kucera parameterisation

$$\begin{aligned} K(Q) &= (V + NQ)(U + MQ)^{-1} \\ &= (\tilde{V} + Q\tilde{N})^{-1}(\tilde{U} + Q\tilde{M}), \forall Q \in \mathcal{RH}_\infty \end{aligned} \tag{9}$$

where Q, which can be any stable system of appropriate input-output dimensions, is a so-called *Youla-Kucera parameter*.

In a dual fashion, it is also possible to characterise all systems stabilised by a fixed controller by means of a so-called *dual Youla-Kucera parameter* $S \in \mathcal{RH}_\infty$. Let some system G, factorised as in (2), be stabilised by a feedback controller K. Then the set of all systems stabilised by K is given by

$$\begin{aligned} \{G : G(S) &= (N + VS)(M + US)^{-1} \\ &= (\tilde{M} + S\tilde{U})^{-1}(\tilde{N} + S\tilde{V}), \quad S \in \mathcal{RH}_\infty\}. \end{aligned} \tag{10}$$

4.1.4. The Hansen Scheme

To motivate the usage of the Youla-Kucera parameterisation in system identification, we first consider normal open-loop identification of the system G. Some input u is applied to the system, and corresponding output measurements y affected by noise n_y are obtained. These measurements are related through

$$y = Gu + n_y$$

and an unbiased estimate of G can be obtained if u and n_y are uncorrelated. Unfortunately, in a closed-loop setting u is *not* uncorrelated with n_y, since the noise is fed back through the controller. To alleviate this, we employ the dual Youla-Kucera factorisation to recast the closed-loop system identification problem into an 'open-loop-like' problem [18].

Assume that a controller K stabilises the plant we wish to identify, and that some nominal plant estimate G is known, factorised as in (3) and (2), respectively. Then the set of all plants stabilised by K can be represented as shown in Fig. 1. Here, $n' = (\tilde{M} + S\tilde{U})n_y$ is the measurement noise that would normally affect the measurements y, relocated in the block diagram to affect the output of the Youla-Kucera parameter instead, and r_1 and r_2 are external excitation signals.

By manipulating the block diagram and using (4), it is possible to check that $y = G(S)u + n_y$. From Figure 1 it is then possible to deduce (see e.g., ([3]), but please note that here we are using positive feedback control) that

$$\zeta = \tilde{U}r_1 + \tilde{V}r_2 \tag{11}$$

$$z = \tilde{M}y - \tilde{N}u \tag{12}$$

Fig. 1. Dual Youla-Kucera parameterisation used for closed-loop system identification

and, obviously, $z = S\zeta + n'$. ζ and z are available from filtered measurements. Furthermore, if n_y is independent of r_1 and r_2, then ζ is independent of n' as well. Also, S is known to be stable due to the dual Youla-Kucera theory (cf. the previous subsection). Thus, it can be seen that although u and y are measured in closed-loop, the identification of S becomes equivalent to an open-loop identification problem.

4.1.5. New Sensor Measurement

We now turn to the problem of identifying new dynamics revealed by a new sensor plugged into an existing control system, as mentioned in the Introduction. As the sensor is plugged into the system, it reveals new information about the plant, including (possibly) extra dynamics that has been unobservable from the existing measurements. Preferably, we wish to identify *only* the new information revealed by the plugged-in sensor, possibly including dynamics introduced by the sensor itself.

Thus, we assume that a nominal model (A, B, C, D) of the 'old' plant dynamics has been found, through first-principles modelling and/or system identification. This model will be denoted G_0 and has the state space realisation (5). G_0 is stabilised by a controller K_0 of the form (6). Now, plugging in a new sensor provides access to a new measurement $y_1 \in \mathbb{R}^{p_1}$, which is affected by the internal (unmeasurable) plant states x as well as the control input u, as depicted in Figure 2. The new measurements are affected by noise $n_{y^\star}$, which is not necessarily uncorrelated with n_y.

The plant–controller ierconnection in Fig. 2 can be represented using the following state space representation. First, we embed G_0 in the augmented plant model

$$G' = \begin{bmatrix} G_0 \\ 0 \end{bmatrix} = \left[\begin{array}{c|c} A & B \\ \hline C & D \\ 0 & 0 \end{array} \right] \tag{13}$$
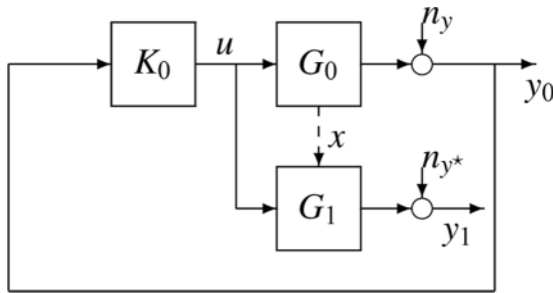
Fig. 2. Plugging in a new sensor reveals the hitherto unobservable subsystem $G^\star$. x denotes the internal state vector of G_0.

which represents the system before introducing the new sensor, and when the new sensor is brought on-line we introduce the new plant

$$G^\star = \begin{bmatrix} G_0 \\ G_1 \end{bmatrix} = \left[\begin{array}{cc|c} A & 0 & B \\ A_{21} & A_{22} & B_2 \\ \hline C & 0 & D \\ C_{21} & C_{22} & D_2 \end{array} \right] \tag{14}$$

where $A_{21}, A_{22}, B_2, C_{21}, C_{22}$ and D_2 are unknown matrices of appropriate dimensions representing G_1 and the couplings from G_0. Note that A_{22} must necessarily be stable, since the closed loop as a whole is stable without feedback from y_1.

Next, we augment the controller as

$$K^\star = \begin{bmatrix} K & 0 \end{bmatrix} = \left[\begin{array}{c|cc} A + BF + LC + LDF & -L & 0 \\ \hline F & 0 & 0 \end{array} \right] \tag{15}$$

and it is easy to check that closing the loop with this controller and either G' or $G^\star$ will yield the same transfer function from r_1 and r_2 to y_0 as before the sensor was introduced.

The augmented coprime factorizations corresponding to (7)–(8) then become

$$\begin{bmatrix} M' & U' \\ N' & V' \end{bmatrix} = \left[\begin{array}{c|ccc} A + BF & B & -L & 0 \\ \hline F & I & 0 & 0 \\ C + DF & D & I & 0 \\ 0 & 0 & 0 & I \end{array} \right] \tag{16}$$

$$\begin{bmatrix} \tilde{V}' & -\tilde{U}' \\ -\tilde{N}' & \tilde{M}' \end{bmatrix} = \left[\begin{array}{c|ccc} A + LC & -(B + LD) & L & 0 \\ \hline F & I & 0 & 0 \\ C & -D & I & 0 \\ 0 & 0 & 0 & I \end{array} \right] \tag{17}$$

for the old system and

$$\begin{bmatrix} M^\star & U^\star \\ N^\star & V^\star \end{bmatrix} = \left[\begin{array}{cc|ccc} A + BF & 0 & B & -L & 0 \\ A_{21} + B_2 F & A_{22} & B_2 & 0 & 0 \\ \hline F & 0 & I & 0 & 0 \\ C + DF & 0 & D & I & 0 \\ C_{21} + D_2 F & C_{22} & D_2 & 0 & I \end{array} \right] \tag{18}$$

$$\begin{bmatrix} \tilde{V}^\star & -\tilde{U}^\star \\ -\tilde{N}^\star & \tilde{M}^\star \end{bmatrix} = \left[\begin{array}{cc|ccc} A + LC & 0 & -(B + LD) & L & 0 \\ A_{21} & A_{22} & -(B_2 + LD_2) & 0 & 0 \\ \hline F & 0 & I & 0 & 0 \\ C & 0 & -D & I & 0 \\ C_{21} & C_{22} & -D_2 & 0 & I \end{array} \right] \tag{19}$$

for the system with the new sensor. In each of the above expressions, the dashed lines indicate how the system matrices on the right-hand side should be partitioned

to correspond to the system blocks on the left-hand side.

Please, note that the two factorizations give rise to the same controller, although they are in general not equal.

Embedding this factorisation in the Hansen framework introduced in Subsection 4.1.4, we can now show the following result.

Theorem 1: *Consider the augmented plant (14) in closed loop with (15). A dual Youla-Kucera parameter system that allows open-loop-like identification of the new sensor dynamics G_1 is given by*

$$S = \left[\begin{array}{c|cc} A_{22} & B_2 & A_{21} \\ \hline C_{22} & D_2 & C_{21} \end{array}\right] \left[\begin{array}{c|cc} A + BF & B \\ \hline F & I \\ I & 0 \end{array}\right] \quad (20)$$

Proof: We take the starting point in (10) and first point out that the augmented system can be written as a function of the old system by means of a particular dual Youla-Kucera parameter $S = \tilde{M}^\star(G^\star - G')M'$. To see this, insert this expression in (10) and use the factorisations $G^\star = (\tilde{M}^\star)^{-1}\tilde{N}^\star$ and $G_0 = N'(M')^{-1}$ to obtain

$$G(S) = (N' + V'\tilde{M}^\star(G^\star - G')M') \times$$
$$(M' + U'\tilde{M}^\star(G^\star - G')M')^{-1}$$
$$= (N' + V'(\tilde{N}^\star M' - \tilde{M}^\star N')) \times$$
$$(M' + U'(\tilde{N}^\star M' - \tilde{M}^\star N'))^{-1}$$

Here we use the Bezout identities $N^\star\tilde{V}' - V'\tilde{N}^\star = 0$, $V'\tilde{M}^\star - N^\star\tilde{U}' = I$ and $\tilde{V}'M' - \tilde{U}'N' = I$ to see that

$$N' + V'(\tilde{N}^\star M' - \tilde{M}^\star N') = \tilde{N}^\star$$

Similarly, from the Bezout identities $M^\star\tilde{U}' - U'\tilde{M}^\star = 0$, $\tilde{M}^\star\tilde{V}' - U'\tilde{N}^\star = I$ and $\tilde{V}'M' - \tilde{U}'N' = I$, we see that

$$M' + U'(\tilde{N}^\star M' - \tilde{M}^\star N') = \tilde{M}^\star$$

and hence $G(S^\star) = G^\star$. Thus, we may proceed to compute an expression for $S^\star$ as follows:

$$S^\star = \tilde{M}^\star(G^\star - G')M'$$
$$= \tilde{M}^\star \left[\begin{array}{cc|c} A & 0 & B \\ A_{21} & A_{22} & B_2 \\ 0 & 0 & 0 \\ \hline C_{21} & C_{22} & D_2 \end{array}\right] M'$$

Now, by looking at $\tilde{M}^\star$ in (19), it is recognised that $\tilde{M}^\star$ receives no input via its first input channel, and its last input channel is simply an identity matrix. Thus we have

$$S^\star = \tilde{M}^\star \left[\begin{array}{cc|c} A & 0 & B \\ A_{21} & A_{22} & B_2 \\ 0 & 0 & 0 \\ \hline C_{21} & C_{22} & D_2 \end{array}\right] M'$$

$$= \left[\begin{array}{cc|c} A & 0 & B \\ A_{21} & A_{22} & B_2 \\ 0 & 0 & 0 \\ \hline C_{21} & C_{22} & D_2 \end{array}\right] \left[\begin{array}{c|c} A + BF & B \\ \hline F & I \end{array}\right]$$

$$= \left[\begin{array}{ccc|c} A & 0 & BF & B \\ A_{21} & A_{22} & B_2F & B_2 \\ 0 & 0 & A + BF & B \\ \hline 0 & 0 & 0 & 0 \\ C_{21} & C_{22} & D_2F & D_2 \end{array}\right]$$

$$= \left[\begin{array}{c} 0 \\ S \end{array}\right]$$

By a simple state transformation, S can be reduced to

$$S = \left[\begin{array}{cc|c} A + BF & 0 & B \\ A_{21} + B_2F & A_{22} & B_2 \\ \hline C_{21} + D_2F & C_{22} & D_2 \end{array}\right]$$

Here, we introduce the filter

$$\Phi = \left[\begin{array}{c|c} A + BF & B \\ \hline F & I \\ I & 0 \end{array}\right]$$

This filter takes ζ defined in (11) as input and yields the output

$$\left[\begin{array}{c} F\xi + \zeta \\ \xi \end{array}\right] = \Phi\zeta$$

where ξ is the state vector of Φ. This allows us to write $S^\star$ as the factorisation $S^\star = \left[\begin{array}{c} 0 \\ \Gamma \end{array}\right]\Phi$, where

$$\Gamma = \left[\begin{array}{c|cc} A_{22} & B_2 & A_{21} \\ \hline C_{22} & D_2 & C_{21} \end{array}\right]. \quad (21)$$

It should be noted that the result could be derived also by exploiting the properties of the observer in the chosen controller parameterization. In fact, the observer would yield $u = Fx + r$ asymptotically as $\hat{x} - x \to 0$. From this observation, both Φ and Γ could have been constructed by inspection. $\lhd$

We thus arrive at our main contribution, the setup for the modified Hansen scheme depicted in Figure 3.

The procedure is straightforward; first generate a data sequence by adding excitation signals through r_1 and r_2, then compute the signals
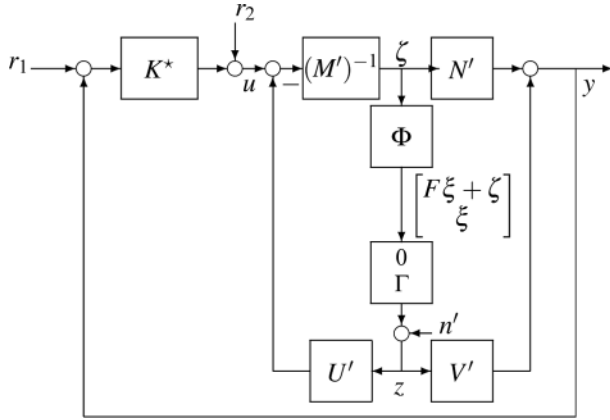
Fig. 3. Hansen scheme for identification of new dynamics.

$$\begin{bmatrix} F\xi + \zeta \\ \xi \end{bmatrix} = \Phi(\tilde{U}'r_1 + \tilde{V}'r_2)$$

and $z = \tilde{M}'y - \tilde{N}'u$ by filtering. Γ can now be obtained by a standard open loop identification method. Once Γ has been found, the extension parameters in (14) are given directly by (21). Alternatively, the plant transfer function can be computed by inserting Γ in the loop in Fig. 3.

It is worth noting that this setup carries over the nice non-correlation qualities of the original Hansen scheme, whereas identifying the transfer function from u to y_1 directly from closed loop data can cause bias problems, especially if the noise is correlated with the noise affecting the control system.

Remark 1: *The signals generated by Φ can have a strong correlation between the elements. This makes it difficult to identify the matrices in Γ independently, although the resulting transfer function from u to y_1 will usually be correct. This issue is inherent to the identification problem itself, and the only solution seems to be to aquire more data.* ◁

Remark 2: *It may be slightly surprising that the setup depicted in Figure 3 still shows the 'old' factorisation, i.e., the factors M', N', U', V' rather than $M^\star, N^\star, U^\star, V^\star$. However, this is due to the connection between the old and the augmented system, i.e., $G^\star = G'(S)$, where, essentially, all the new dynamics is isolated in the S_1-parameter.* ◁

4.1.6. Simulation Example

We now illustrate the feasibility of the identification scheme by a numerical example. We consider the discrete-time system

$$x_{k+1} = Ax_k + Bu_k$$
$$y_k = Cx_k + n_y$$

where

$$A = \begin{bmatrix} 0.7 & 0.7 & 0.4 \\ 0.65 & 0.3 & 0.09 \\ -0.8 & 0.27 & 0.94 \end{bmatrix}, \quad B = \begin{bmatrix} 0.07 \\ 0.03 \\ 0.1 \end{bmatrix}$$

$$C = \begin{bmatrix} 1 & 0 & 0 \end{bmatrix}$$

and n_y is a Gaussian white noise signal with variance 0.0050. The system is open-loop unstable (with poles in $z = -0.1084, z = 1.0242 \pm 0.4047j$), so it is not possible to disconnect the controller to obtain good data for identification. This system has been chosen because it poses a relatively difficult identification task when we are only allowed to impose mild excitation signals.

A stabilizing observer-based controller for the system has been found using standard optimal control design methods. The feedback and observer gains were found to

$$F = \begin{bmatrix} -1.5 & -2.6 & -2.7 \end{bmatrix} \text{ and } L = \begin{bmatrix} -0.36 \\ -0.27 \\ 0.23 \end{bmatrix}$$

respectively.

The system is then augmented with a new sensor, which has its own dynamics, feedthrough from the control input, etc. It is described by the following augmented system matrices specified in (14):

$$A_{21} = \begin{bmatrix} 0 & 0.1 & 0.3 \end{bmatrix}, A_{22} = 0.9, B_2 = 0.094$$
$$C_{21} = \begin{bmatrix} 0 & 0 & -0.4 \end{bmatrix}, C_{22} = 1.2, D_2 = 0.2$$

Furthermore, it is affected by Gaussian noise $n_{y^\star}$, which is correlated with n_y as given by the covariance matrix

$$E\left\{ \begin{bmatrix} n_y \\ n_{y^\star} \end{bmatrix} \begin{bmatrix} n_y & n_{y^\star} \end{bmatrix} \right\} = \begin{bmatrix} 0.0025 & 0.0025 \\ 0.0025 & 0.005 \end{bmatrix}$$

All the information about the new sensor is considered unknown at the point where the sensor is brought on-line.

We now apply pseudo-random excitation signals r_1 and r_2 to the control loop as indicated in Fig. 3. Fig. 4 shows plots of the excitation signals, the control input, as well as the 'old' output y_0 and the new sensor output y_1. As can be seen from the figure, the excitation signals are of small amplitude compared to u and y and are mainly in the low end of the frequency spectrum, i.e., they do not interfere aggressively with the closed-loop operation of the plant.

Next, we filter r_1, r_2, u and y_1 as given in the previous subsection and use the filtered signals ζ and z for system identification of the S parameter system. Fig. 5 shows a Bode plot of the identified system together with the corresponding Bode plot of the true S (computed using equation (1), with the true parameters inserted). As can be seen, there is very good agreement between the two, especially for frequencies up to 1 rad/sec.

For comparison purposes, we also perform a 'direct' system identification, i.e. identifying a transfer function from u to y_1 using these signals directly. We then compute the transfer function from u to y_1 for the true system, using the S-parameter found above, and the new 'direct' identified model. Bode plots of the results are shown in Fig. 6, from which it is very apparent that the Hansen-scheme-based model is much closer to the real system than the 'direct' identified model. This is most likely because u and y_1 are correlated through the old plant-controller loop, and due to the fact that the noise signals are correlated.

Finally we take a look at the identified Γ in Fig. 7, comparing it to the real Γ given by (21). As seen, the fit is very poor, which is not surprising, see Remark 1. Additional tests indicate that using a much larger data sequence will make the estimated Γ converge to the correct one, but as seen above, this is not necessary if

Fig. 4. Data sequences for identification. From the top: excitation sequences r_1 and r_2, control signal u, old output y_0 and new output y_1.
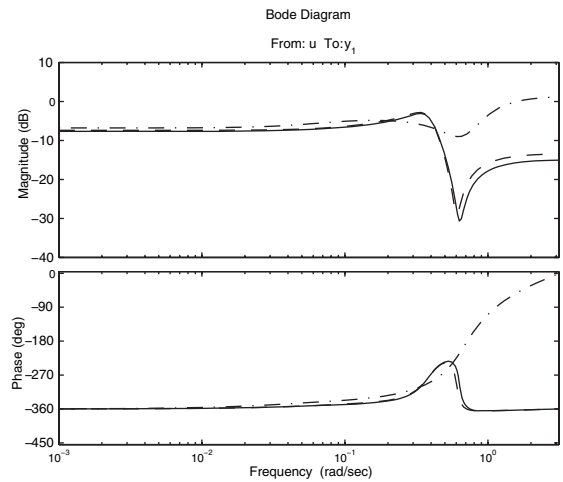
Fig. 6. Bode plot of transfer function from u to y_1. Solid: Real. Dashed: Inserting S identified by Hansen scheme. Dotted: Identified directly.

Fig. 5. Bode plot of S. Solid: True S. Dashed: Identified by Hansen scheme.
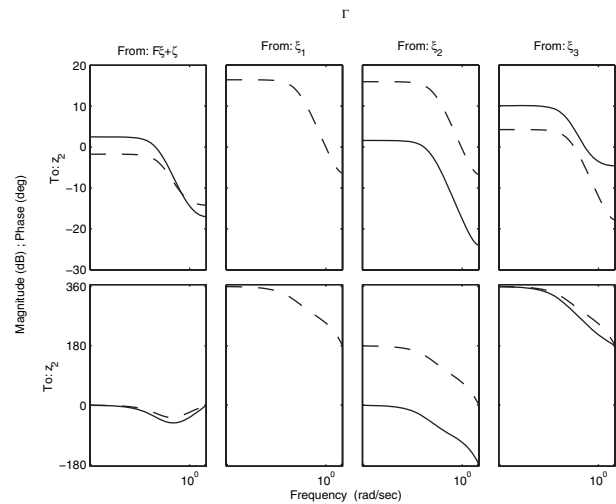
Fig. 7. Bode plot of Γ. Solid: Computed from (1). Dashed: Identified by Hansen scheme.

we are only interested in getting the correct transfer function to the new output.

In conclusion, we have demonstrated that the proposed scheme can identify new dynamics for relatively difficult unstable systems with only a small amount of excitation.

4.1.7. Discussion

Closed-loop system identification is much more difficult than open-loop system identification, due to the fact that inputs and noise cannot be considered uncorrelated because of the controller feedback. The so-called Hansen scheme is a factorisation-based approach to alleviate some of these difficulties by taking the starting point in a 'nominal' system model and identifying the unknown dynamics by means of a dual Youla-Kucera parameter in an essentially open-loop setting.

This subsection showed how the Hansen scheme can be extended to deal with new measurements that become available during online operation. The original plant is embedded in a larger system, in which hitherto unobservable dynamics is revealed by letting a new sensor come online. It was then shown how the identification of the newly revealed dynamics is equivalent to the identification of a surprisingly simple dual Youla-Kucera parameter.

The novel scheme was shown to be superior to simple, 'direct' system identification of the new dynamics in a simple example. One might argue that similar results can be obtained by generating signals through a simulation of the closed loop with only excitation signals as inputs. However, formulating the problem in the Youla–Kucera–Hansen framework paves the way for controller redesign and transfer along the lines demonstrated in [7].

4.2. Stable Controller Reconfiguration through Terminal Connections

The results in this subsection is largely based on the paper [38].

All medium- to large-scale automation systems, such as power plants, refineries, factories, supermarkets or even large ships, invariably have control systems to handle the automated processes, such as production facilities, chemical batch processing, climate control or steam production. These control systems are often designed at the time of commissioning of the plant and tend to rely on PLCs or similar hardware to implement classically designed (and often conservatively tuned) control loops. However, as time

goes by and new technology and knowledge becomes available, it may become desirable to introduce new sensor and/or actuator hardware.

There can be various reasons for this: wear and tear on the existing devices; new technology that can supplement with better or cheaper measurements or actuation becomes available; better knowledge about the process dynamics invites more precise control; etc.

On the other hand, there may also be a strong argument for maintaining the existing control system, since it has a proven track record, and designing an entirely new control system from the bottom up is likely to be very costly both in terms of commissioning and operation stop. Furthermore, in addition to linear controller dynamics, the original controller may be part of a safety critical interlocking circuit as well.

The contribution of this subsection is to provide a method of introducing new control components in a smooth manner, which provides stability guarantees during the transition phase, and which retains the original control structure intact.

In ([35]) a gain scheduling method was presented which solves this problem, but the implementation is of a rather high order, and the performance during transitions can be poor.

The method presented in this subsection relies on the Youla-Kucera parametrization of all stabilizing controllers for a given plant. This methodology has the advantage of ensuring stability during the transition, and that the performance transfer function is affine in the design parameter, which means that the design problem has an open loop nature and that good performance can be expected during transition between controllers.

Subsection 4.2.1 provides the necessary background information on the Youla-Kucera parameterisation. Subsections 4.2.2 and 4.2.3 present the novel method for modifying controller behaviour. In Subsection 4.2.4, a simulation example is presented, where the controller is modified after a new actuator is introduced.

4.2.1. Controller parameterisation

This subsection gives a short introduction to some basic concepts of coprime factorisation and the Youla-Kucera parameterisation of stabilising controllers. See ([41, 24, 3, 29]) for further details.

Consider the control loop in the left part of Figure 8 and assume that the controller K_0 stabilises the system G. Factorise the lower right part of G as (2) with $N, M, \tilde{M}, \tilde{N} \in \mathcal{RH}_\infty$, and K_0 as
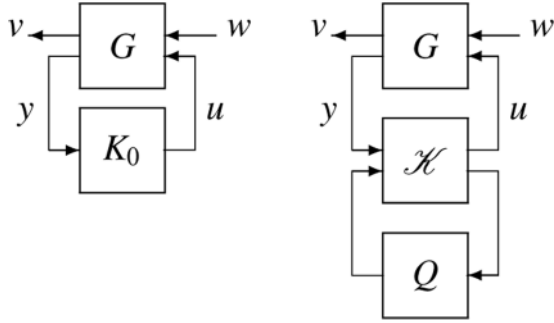
$$K_0 = UV^{-1} = \tilde{V}^{-1}\tilde{U} \tag{22}$$

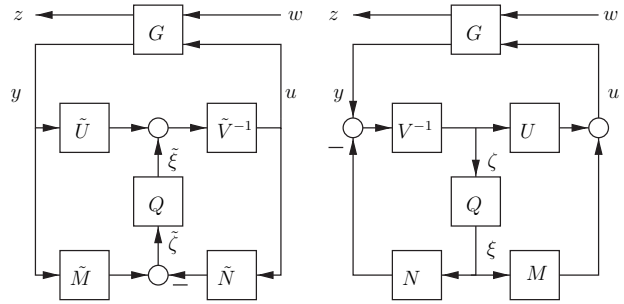**Fig. 8.** Left: The interconnection of the system G and the controller K_0. Right: Controller implemented as $K(Q) = \mathcal{K} \star Q$.

Fig. 9. Left and right coprime factorisation-based Youla–Kucera parameterisation of all stabilising controllers.

where $U, V, \tilde{U}, \tilde{V} \in \mathcal{RH}_\infty$, with the factors chosen to satisfy the double Bezout identity

$$\begin{bmatrix} \tilde{V} & -\tilde{U} \\ -\tilde{N} & \tilde{M} \end{bmatrix}\begin{bmatrix} M & U \\ N & V \end{bmatrix} = \begin{bmatrix} M & U \\ N & V \end{bmatrix}\begin{bmatrix} \tilde{V} & -\tilde{U} \\ -\tilde{N} & \tilde{M} \end{bmatrix} = \begin{bmatrix} I & 0 \\ 0 & I \end{bmatrix}.$$

All stabilising controllers for G can now be parameterised according to the Youla–Kucera parameterisation

$$K(Q) = \mathcal{K} \star Q = K_0 + \tilde{V}^{-1}Q(I + V^{-1}NQ)^{-1}V^{-1},$$

with $Q \in \mathcal{RH}_\infty$, i.e., $G \star K(Q)$ is stable for any stable Q and for any stabilising controller K_i, a stable Q exists so that $K(Q) = K_i$. This linear fractional transformation setup is depicted in the right part of Fig. 8, and, due to the Bezout identity, can also be implemented as in Fig. 9.

Thus, it is possible to implement a given controller as a function of a stable parameter system Q based on another stabilising controller, as depicted in the right part of Fig. 8. As stated in [30] this implies that it is possible to change between two controllers online, say, from a nominal controller K_0 to another controller K_1, in a smooth fashion *without losing stability*, by scaling the Q parameter by a factor $\gamma \in [0; 1]$.

One interesting feature of the parameterisation is that the performance transfer function from w to z is affine in Q, i.e.

$$T_{zw} = T_1 + T_2 Q T_3, \tag{23}$$

also illustrated in Fig. 10, where T_1, T_2, and T_3 are stable transfer functions. Thus, a control design can be carried out by finding a stable Q that minimises T_{zw} in some sense. This is known as a model matching problem [17].

Alternatively, if a desired transfer function for a new stabilizing controller K_1 has been obtained, $K(Q) = K_1$ can be realised by factoring $K_1 = \tilde{V}_1^{-1}\tilde{U}_1$ with

Fig. 10. Classical model matching setup.

$$\begin{bmatrix} \tilde{V}_1 & -\tilde{U}_1 \\ -\tilde{N} & \tilde{M} \end{bmatrix}\begin{bmatrix} M & U_1 \\ N & V_1 \end{bmatrix} = \begin{bmatrix} M & U_1 \\ N & V_1 \end{bmatrix}\begin{bmatrix} \tilde{V}_1 & -\tilde{U}_1 \\ -\tilde{N} & \tilde{M} \end{bmatrix} = \begin{bmatrix} I & 0 \\ 0 & I \end{bmatrix},$$

and setting [8]

$$Q = \tilde{U}_1 V - \tilde{V}_1 U = \tilde{V}_1(K_1 - K_0)V. \tag{24}$$

Once a Q has been designed, the affine dependence also means that if Q is scaled by γ as mentioned above, then the performance will change in a predictable way for values of γ between 0 and 1. (In fact, stability will be preserved even for quickly time-varying γ [19], but that is not essential here.)

4.2.2. Controller modification

We now turn our attention to a situation, where we wish to modify the controller behaviour but without removing the original controller. The reasons for the desired change can be numerous. The system may have changed due to equipment being added or replaced or simply due to wear and tear, or maybe a better understanding of the system has been obtained.

As mentioned in the introduction, the reasons for desiring to keep the original controller in the loop can also be numerous. It may for instance contain supervisory logic that we do not wish to replicate. Also, the operator will often be wary of removing a functioning controller with an entirely new replacement. Instead, adding a controller to the original one and slowly turning it on would be much more appealing.

We assume that the original controller still stabilises the system, but we cannot access the inside of it, as Fig. 9 would suggest is needed to use a Youla–Kucera
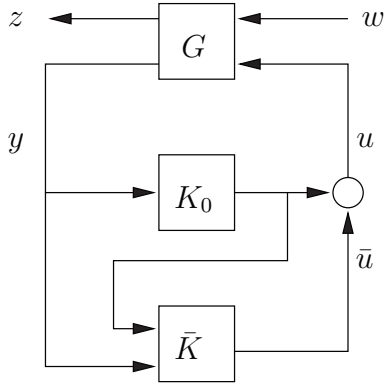
Fig. 11. Modifying a controller through the control signal terminal.

Fig. 12. Controller parameterisation modified for connection to terminals of existing controller.

parameterisation. Rather, the additional controller, $\bar{K}$, must be applied at the terminals of the existing controller as shown in Fig. 11.

Thus, the task is to develop a method for designing an additional controller to be applied at the terminals of the original controller, which will improve the performance. It must be possible to perform the switch gradually while maintaining stability, so that the process can be monitored.

By modifying the Youla–Kucera parameterisation in Fig. 9, we arrive at the two possible setups in Fig. 12. Here, the original controller, K_0 is kept in place and is only accessed at the terminals. Stability of $\bar{Q}$ still implies stability of the closed loop, but not all stabilising controllers are parameterised by a stable $\bar{Q}$:

Theorem 2: *Let $G_{yu} = \tilde{M}^{-1}\tilde{N}$ be a coprime factorisation of a system, and assume that $K_0 = \tilde{V}_0^{-1} \tilde{N}_0 = U_0 V_0^{-1}$, is a stabilizing controller, i.e. $G \star K_0 \in \mathscr{RH}_\infty$. Consider a second controller $K_1 = \tilde{V}_1^{-1}\tilde{N}_1 = U_1 V_1^{-1}$. Then*

$$G \star K_1 \in \mathscr{RH}_\infty \wedge V_0^{-1} V_1 \in \mathscr{RH}_\infty \qquad (25)$$

$$\Updownarrow$$

$$\exists \bar{Q} \in \mathscr{RH}_\infty : K_1 = (I + \bar{Q}\tilde{N})^{-1} \begin{bmatrix} I & \bar{Q}\tilde{M} \end{bmatrix} \begin{bmatrix} K_0 \\ I \end{bmatrix} \qquad (26)$$

i.e., (26) is a parameterization of all stabilizing controllers that include the right half plane (RHP) pole structure of K_0.

Proof: First, assume that a controller K_1 satisfying (25) is given where, without loss of generality, we can assume that the parameterizations given satisfy the double Bezout identity. Define

$$\bar{Q} = U_1 - U_0 V_0^{-1} V_1 \in \mathscr{RH}_\infty$$

From (25) we infer $\bar{Q} \in \mathscr{RH}_\infty$. With this choice, we obtain:

$$(I + \bar{Q}\tilde{N})^{-1} \begin{bmatrix} I & \bar{Q}\tilde{M} \end{bmatrix} \begin{bmatrix} K_0 \\ I \end{bmatrix}$$

$$= (I + (U_1 - U_0 V_0^{-1} V_1)\tilde{N})^{-1} \begin{bmatrix} I & (U_1 - U_0 V_0^{-1} V_1)\tilde{M} \end{bmatrix} \begin{bmatrix} K_0 \\ I \end{bmatrix}$$

$$= (M\tilde{V}_1 - U_0 V_0^{-1} V_1 \tilde{N})^{-1} \begin{bmatrix} U_0 V_0^{-1} - U_0 V_0^{-1} V_1 \tilde{M} + U_1 \tilde{M} \end{bmatrix}$$

$$= (M\tilde{V}_1 - U_0 V_0^{-1} N \tilde{V}_1)^{-1} \begin{bmatrix} -U_0 V_0^{-1} N \tilde{U}_1 + M\tilde{U}_1 \end{bmatrix}$$

$$= \tilde{V}_1^{-1}(M - U_0 V_0^{-1} N)^{-1} \begin{bmatrix} -U_0 V_0^{-1} N + M \end{bmatrix} \tilde{U}_1$$

$$= \tilde{V}_1^{-1} \tilde{U}_1 = K_1$$

Conversely, assume that K_1 is given by:

$$K_1 = (I + \bar{Q}\tilde{N})^{-1} \begin{bmatrix} I & \bar{Q}\tilde{M} \end{bmatrix} \begin{bmatrix} K_0 \\ I \end{bmatrix} \qquad (27)$$

We rewrite (27) as

$$K_1 = (I + \bar{Q}\tilde{N})^{-1} \begin{bmatrix} V_0^{-1} U_0 + \bar{Q}\tilde{M} \end{bmatrix}$$

$$= (V_0 + V_0 \bar{Q}\tilde{N})^{-1} \begin{bmatrix} U_0 + V_0 \bar{Q}\tilde{M} \end{bmatrix}$$

$$= (V_0 + Q\tilde{N})^{-1} \begin{bmatrix} U_0 + Q\tilde{M} \end{bmatrix}$$

with $Q = V_0 \bar{Q} \in \mathscr{RH}_\infty$, and we see that K_1 is a stabilizing controller due to the Youla–Kucera theorem.

In order to prove that V_1 contains the RHP zero structure of V_0, we rearrange (27) into

$$(I + \bar{Q})U_1 V_1^{-1} = U_0 V_0^{-1} + \bar{Q}\tilde{M}$$

and further into

$$(I + \bar{Q})U_1 - \bar{Q}\tilde{M}V_1 = U_0 V_0^{-1} V_1 \qquad (28)$$

Since the left hand side of (28) is stable, so is the right hand side. Due to coprimeness of U_0 and V_0 there occur no RHP cancellations in forming the product $U_0 V_0^{-1}$, and since V_1 is stable, the product $V_0^{-1} V_1$ itself must be stable. $\lhd$

Thus, the setup in the left part of Fig. 12 corresponding to (26) parametrises all stabilising controllers containing the same unstable poles as K_0,
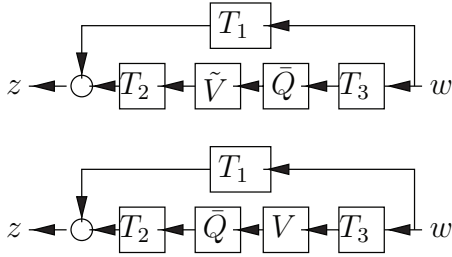
Fig. 13. Modified model matching setup.

i.e. we cannot move these unstable poles, but we can introduce new ones.

As with the Youla–Kucera parametrisation, the performance transfer function is affine in $\bar{Q}$, and the controller can still be designed by a model matching method, where the T_1, T_2, and T_3 transfer functions are the same as in Fig. 10, but V or $\tilde{V}$ are introduced as shown in Fig. 13.

In particular cases, T_2 and T_3 will be invertible and $\bar{Q}$ can be designed from

$$\bar{Q} \approx -\tilde{V}^{-1}T_2^{-1}T_1T_3^{-1}. \tag{29}$$

If exact equality could be achieved, this would imply $T_{zw} = 0$, but of course the inverses will usually have to be approximated to obtain a stable $\bar{Q}$.

As in (24), the design can also be done by designing a desired K_1 and finding Q solving

$$\bar{Q}V = \tilde{U}_1 V - \tilde{V}_1 U = \tilde{V}_1(K_1 - K_0)V, \tag{30}$$

or

$$\tilde{V}\bar{Q} = \tilde{U}_1 V - \tilde{V}_1 U = \tilde{V}_1(K_1 - K_0)V, \tag{31}$$

but since V and $\tilde{V}$ usually are not inversely stable, $\bar{Q}$, must be chosen as a stable approximation.

Note that the implementation in Fig. 12 only requires the factorised plant model, although the model of the original controller is of course needed for the design of $\bar{Q}$.

As an aside, we note that it is possible to fully parameterise all stabilising controllers without doing any factorisation as shown in Fig. 14 [34]. This can still be done by only accessing the terminals. Here, a stable Q implies a stable closed-loop, and vice versa. It does however require copying the controller and plant models, and the resulting implementation could be of a very high order. On the other hand, this parameterisation makes it possible to deal with nonlinear plants and controllers, which will be the topic of further research.
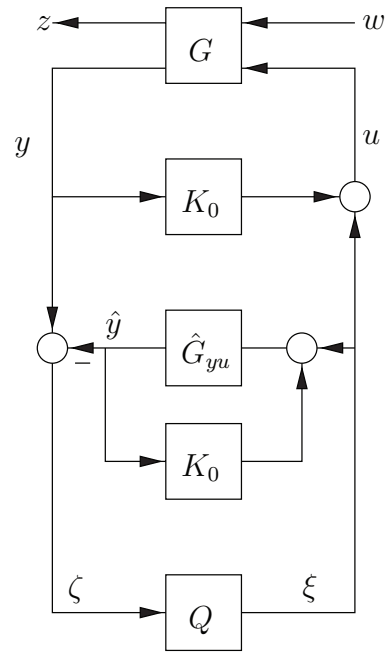
Fig. 14. Pre-stabilised internal model control.

4.2.3. Adding sensors and actuators

The main purpose of this work is to arrive at methods for automatic reconfiguration when new sensors and actuators are plugged in. The above method works for more general changes to the system, but in case of an additional sensor or actuator, we simply append the system model G with the new part, and add zero columns or rows to the model of the original controller before doing the factorisation.

Given a state space factorisation, [29] provides extensions to the factors which preserve the original parts when adding sensors and actuators. However, for now we are not concerned with the particular structure of the factors.

4.2.4. Simulation example

In the buffer tank example shown in Fig. 15, the fluid level M is controlled by a pump and a valve in series. The tank is disturbed by an unmeasured load flow $\dot{m}_L$. The only measurement is the fluid level.

In [39] a first principles model was linearised to obtain the model shown in Fig. 16.

At the original design, the valve was manually operated, meaning that the control system could only use the pump to control the fluid level. Since it was desired to suppress ramp disturbances in the load, a controller, K_0, with a double integrator was designed:
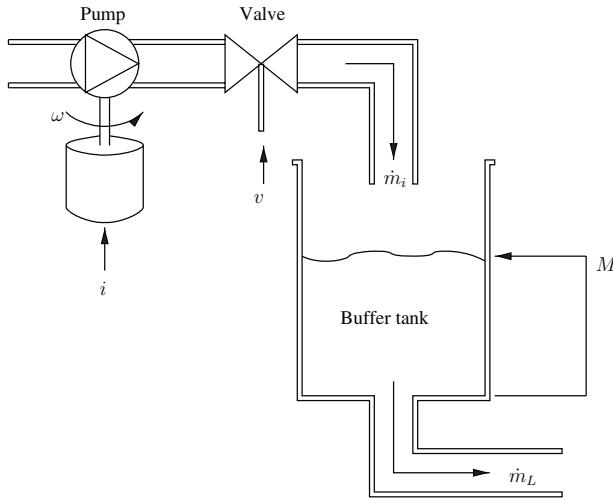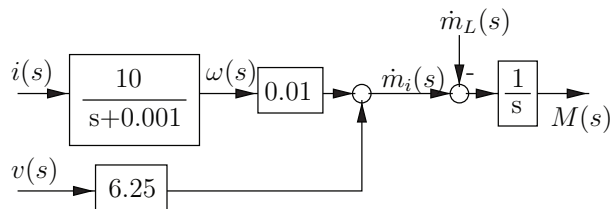
Fig. 15. Example system.

Fig. 16. Linearised model.

$$u(s) = \begin{bmatrix} i(s) \\ v(s) \end{bmatrix} = K_0(s)M(s) \tag{32}$$

with

$$K_0(s) = \begin{bmatrix} \dfrac{-0.1(s+0.01)(s+0.001)^2}{s^2(s+0.1)} \\ 0 \end{bmatrix}. \tag{33}$$

After some time, it is found that the performance is not satisfactory and that the strain on the pump is too high. Therefore the manual valve is replaced with an electronically controlled one. However, we still wish to keep the original K_0 in the loop for several reasons. First of all, the controller contains some safety critical logical circuitry in addition to the linear controller. Secondly, in periods with very small disturbances, we may want to be able to fully open the valve and only use the pump for control in order to save energy. Furthermore, the plant operator will be most happy, if the new controller can be tuned in slowly, so that the effects can be monitored.

Thus, the new controller should be implemented as in Fig. 11, and it should be possible to scale the influence of it while preserving stability and a satisfactory performance. We therefore choose to implement the additional controller as in Fig. 12. The disturbance w is the load flow, and the performance output is chosen as the fluid level and the pump current deviations, i.e. we want to maintain a stable level without using the pump a lot. With this choice, both T_2 and T_3 in Fig. 13 are invertible, so $\bar{Q}$ can be designed using (29). $\tilde{V}^{-1} T_2^{-1} T_1 T_3^{-1}$ has poles in $s = 0$, and is approximated by moving these slightly to the left in s-plane.

Fig. 17 shows the effects of the additional controller. The top row shows the response with the original controller to a step in the load flow. The fluid level drops, resulting in an increased pump speed. Due to the slowness of the pump, it takes hundreds of seconds before the level is returned to normal. The bottom row shows the results of a similar load flow step but with the additional controller applied. Now the valve immediately reacts to a fluid level drop and almost completely removes the effects while maintaining the same pump speed. The middle rows show the results for different scalings of the additional controller. An important point is that a good performance is ensured for these intermediate steps, making it possible to perform a gradual change from one controller to the other.

It is also worth noting that although step disturbances give no steady state error, the additional controller does not contain integrators in itself, but borrows these from the original controller, transferring the action from the pump to the valve.

In practice, it may be difficult to implement a $\bar{Q}$ designed from (29), since it tends to have a high order and a large gain. In this particular example it would probably give more moderate gains if the valve action was included in the performance output z. Then, T_2 would no longer be invertible, and a more traditional model matching method should be used.

4.3. A sensor fusion approach for exploiting new measurements in an existing controller

This subsection is largely based on the paper [36].

An advanced (typically model based) control system is usually expensive to implement for a large scale system, as e.g. obtaining and verifying the model consumes significant time, and so does the controller design, verification and testing.

One of the blocking factors for spreading advanced control technology even more widely is the fact that real plants are not static. Most large plants are constantly being re-engineered. Components will be replaced with other components that are not identical. Subsystems might be added or removed. Instrumentation might be changed in terms of adding or removing sensors and/or actuators.
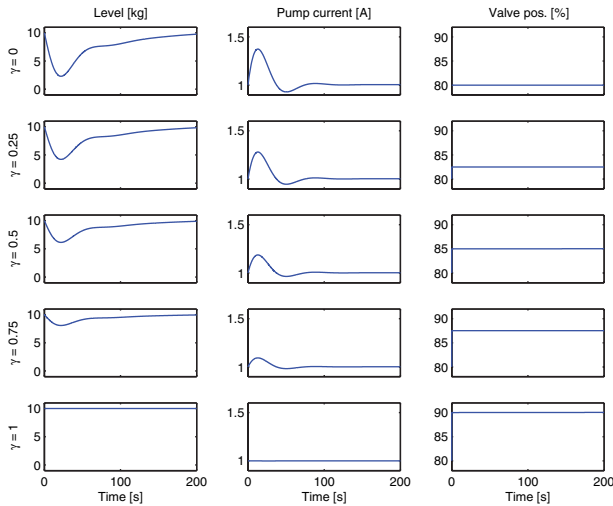
Fig. 17. Simulation of a step in the load flow. Top row: Original controller. Bottom row: Modified controller.

Fig. 18. Proposed architecture with additional observer. Solid box: system; Dotted box: new observer; Dashed box: original controller.

Unfortunately, it has been studied only very sparsely in the control community how to design control systems, that are robust to the kind of changes outlined above. This means, that the expenses to the control system will accumulate, as the control system needs to be re-engineered along with the dynamic changes of the plant itself. To some industries, this added cost might be preventive.

In a number of recent papers, this challenge has been addressed, see [9, 14, 21, 23, 27, 38]. In these papers, it is in particular studied, how an advanced control system can be equipped with intelligence, that facilitates that it adjusts itself automatically in the face of changes e.g. in instrumentation.

Along this line of research, in the present subsection it is studied how to modify a controller, once it is allowed to exploit a larger number of sensors. In particular, it is assumed that the control signal should still be generated by the existing (original) controllers. Thus, only the inputs to the controllers are allowed to change with the new measurements. This could be relevant in a number of cases, e.g. if the existing controller is integrated in the actuator hardware, or if the existing control algorithm is embedded in a block of software which is inaccessible for various reasons, e.g. for practical reasons, for reasons of software vendor legal issues, or due to quality management rules.

The approach taken will be sensor fusion based, see e.g.[13, 15]. In a wide range of literature it is described how to implement controllers based on sensor fusion, see e.g. [1] and references therein. In the present subsection, however, we specifically address the situation of fusing new measurements with existing ones in order to modify the inputs to an existing controller, such that the overall performance increases.
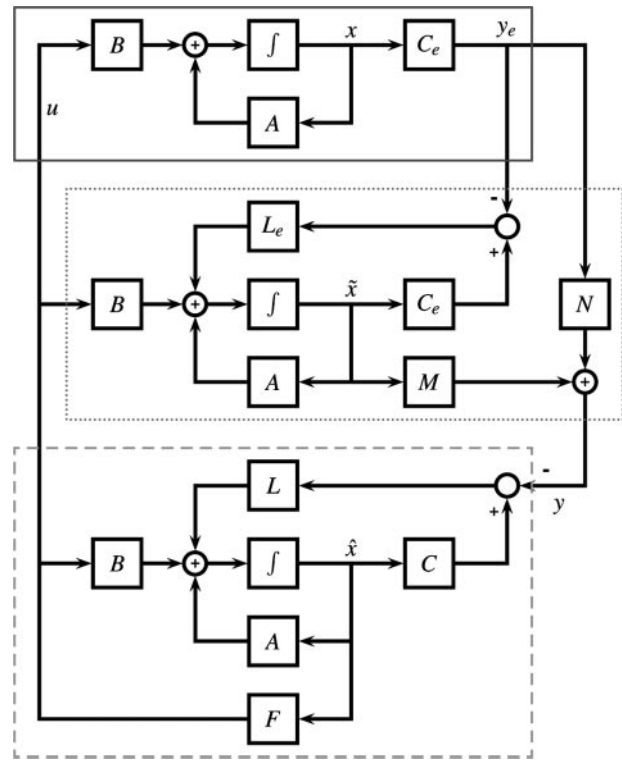
To that end, an observer based architecture will be proposed below. For this architecture, a (single) separation principle will be demonstrated, allowing the added observer poles to be designed separately. Further, it will be shown that if certain constraints are imposed on the design parameters, a double separation principle will hold, where all the involved poles can be designed separately as either observer poles or state feedback poles.

A numerical example illustrates both a design procedure based on the single and double separation principle. It turns out, that the general method in most cases can lead to better performance than the method based on the double separation principle.

4.3.1. An observer based approach

In the sequel, we shall describe an approach to modify the inputs to a controller in order to exploit additional measurements, which have been added. The approach will be based on the architecture illustrated in Fig. 18. In this architecture, the inputs to the original controller, which is assumed to be a full order observer based controller, are generated as outputs from a new observer, including a direct feed-through term from the measurements.

The original system to be controlled is described by a state space model of the form:

$$\dot{x} = Ax + Bu$$
$$y = Cx \tag{34}$$

After adding new sensors, the system will be described by a state space model of the form:

$$\dot{x} = Ax + Bu$$
$$y_e = C_e x \tag{35}$$

where typically C_e will take the form:

$$C_e = \begin{pmatrix} C \\ C_{\text{new}} \end{pmatrix}$$

The existing compensator is assumed to be a full-order observer based controller:

$$\dot{\hat{x}} = A\hat{x} + Bu + L(C\hat{x} - y)$$
$$u = F\hat{x} \tag{36}$$

This assumption is fairly mild, in fact under mild conditions, any controller can be written as an observer based controller, see [2]. In order to exploit the new outputs, an additional observer is introduced:

$$\dot{\tilde{x}} = A\tilde{x} + Bu + L_e(C_e\tilde{x} - y_e)$$
$$y = M\tilde{x} + Ny_e \tag{37}$$

where L_e, M and N are design parameters, see below.

To summarize the properties of the proposed architecture, we have the following separation principle.

Theorem 3: *Consider the configuration illustrated by Figure 18, where a system given by the state space model (35) is controlled by an observer based compensator, designed for an original system (34), where the input to the controller is generated by an additional observer of the form (37).*

This closed loop system has poles given by the eigenvalues of the two matrices:

$$A + L_e C_e \quad \text{and} \quad \begin{pmatrix} A + BF & BF \\ L(C - M - NC_e) & A + LC \end{pmatrix}$$

In the special case, where M and N are chosen to fulfill

$$M + NC_e = C \tag{38}$$

then the closed loop system satifies a 'full' separation principle, i.e. the closed loop poles are given by the eigenvalues of the three matrices:

$$A + BF, \quad A + L_e C_e \quad \text{and} \quad A + LC$$

which means that observer and feedback gains can be designed independently, if only the closed loop poles are of concern.

Proof: The proof follows directly from manipulations of the closed loop state space formulation, which is given by:

$$\begin{pmatrix} \dot{x} \\ \dot{\tilde{x}} \\ \dot{\hat{x}} \end{pmatrix} = \begin{pmatrix} A & 0 & BF \\ -L_e C_e & A + L_e C_e & BF \\ -LNC_e & -LM & A + LC + BF \end{pmatrix} \begin{pmatrix} x \\ \tilde{x} \\ \hat{x} \end{pmatrix}$$

Applying the state space transformation:

$$x_{\text{new}} = \begin{pmatrix} I & 0 & 0 \\ I & I & 0 \\ I & 0 & I \end{pmatrix} \begin{pmatrix} x \\ \tilde{x} \\ \hat{x} \end{pmatrix}$$

yields a new state space model for the closed loop system of the form:

$$\dot{x}_{\text{new}} = A_{\text{new}} x_{\text{new}}$$

where

$$A_{\text{new}} = \begin{pmatrix} A + BF & 0 & BF \\ 0 & A + L_e C_e & 0 \\ L(C - M - NC_e) & -LM & A + LC \end{pmatrix}$$

From this it is clearly seen, that the set of closed loop eigenvalues can be separated into the union of the sets of eigenvalues of the following two matrices:

$$A + L_e C_e \quad \text{and} \quad \begin{pmatrix} A + BF & BF \\ L(C - M - NC_e) & A + LC \end{pmatrix}$$

In the special case, where M and N are chosen to fulfill

$$M + NC_e = C$$

then the second matrix above specializes to:

$$\begin{pmatrix} A + BF & BF \\ 0 & A + LC \end{pmatrix}$$

from which it is seen that we have a full separation of the closed loop eigenvalues into the eigenvalues of the three matrices:

$$A + BF, \quad A + L_e C_e \quad \text{and} \quad A + LC$$

$$\lhd$$

The intuition for the condition (38) is that the new input to the original controller is generated as a interpolation between the original measurements and

an estimate of the original measurements based on the original and the new measurements. Therefore, if the new measurements are of a poor quality, (38) will specialize to

$$NC_e \approx C, \quad M \approx 0$$

On the other hand, if the new measurements are highly superior to the original measurements, (38) will specialize to

$$M \approx C, \quad N \approx 0$$

Although Theorem 3 suggests that the new observer can be designed independently of the existing controller, it should be noted, however, that the new observer can introduce a significant phase shift, which should be taken into consideration in the design process. In fact, practical experience with the method shows that better results can in general be achieved, if M and N are chosen, such that (38) is *not* satisfied.

It should also be noted, that if (38) is not satisfied, then $\tilde{x}$ is still an estimate of x, whereas $\hat{x}$ can not be assumed to be an estimate of x. Thus, if the original controller to some extent relies on having a reliable estimate, then the M and N should be chosen to satisfy (38).

It is not in itself surprising that a better result can be achived, if (38) is not imposed as a constraint. In fact, in that case, the combined new controller, consisting of the original controller and the new observer, is allowed to increase the gains of the system, based on the improved measurement situation. The main disadvantage of pursuing a design that does not satisfy (38) is that the link between design parameters and design objectives becomes more complicated. In that case, typically an optimization procedure will be involved in the design with M, N, L_e as parameters. The objective function should reflect the original control objectives.

4.3.2. Example

In this subsection, we consider a random third order example, described by the following state space description:

$$\dot{x} = Ax + Bu$$
$$y = Cx$$

where

$$A = \begin{pmatrix} -0.5277 & -0.0244 & -0.8930 \\ -0.5113 & -0.6620 & -1.3970 \\ 0.3326 & -1.1656 & 0.4068 \end{pmatrix},$$

$$B = \begin{pmatrix} -1.3676 \\ -1.1816 \\ 1.5603 \end{pmatrix}, \quad C = (\,2.1565 \quad 2.2956 \quad -0.6431\,)$$

For this system, an observer based controller is designed such that the feedback poles are $\{-1, -2, -3\}$ and the observer poles are $\{-4, -5, -6\}$. With positive feedback convention (see Figure 18), this is achieved by:

$$F = (\,-8.6858 \quad 6.4133 \quad -6.1004\,),$$

$$L = \begin{pmatrix} 11.6089 \\ -14.6535 \\ 8.7287 \end{pmatrix}$$

giving rise to the following nominal controller

$$K(s) = \frac{248.1s^2 + 279.8s - 193.3}{s^3 + 20.22s^2 - 1493s - 2216} \tag{39}$$

(which is likely to cause implementation challenges, as it is open loop unstable and non-minimum phase. That is, however, besides the point).

A new sensor is introduced, such that the extended system is described by:

$$\dot{x} = Ax + Bu$$
$$y_e = C_e x$$

where

$$C_e = \begin{pmatrix} 2.1565 & 2.2956 & -0.6431 \\ \hline -1.4058 & 1.3159 & -1.4420 \end{pmatrix}$$

In the sequel, we shall illustrate two design approaches that design a new input for the nominal controller (39) using the additional sensor by means of a new observer, introduced between the plant and the original controller.

As a first design approach, we shall try to use the full separation approach of Theorem 3. In this case, we will use a fully filtered input to the original controller, meaning that we choose $N = 0$. From the necessary and sufficient condition for separation (38), we then obtain:

$$M = C - N * C_e = C$$

The new observer is designed to have observer poles in $\{-70, -80, -90\}$, which is obtained by the observer gain:

$$L_e = 10^3 \times \begin{pmatrix} -0.5476 & 0.0454 \\ 0.8009 & -0.0521 \\ 1.2697 & -0.0361 \end{pmatrix}$$
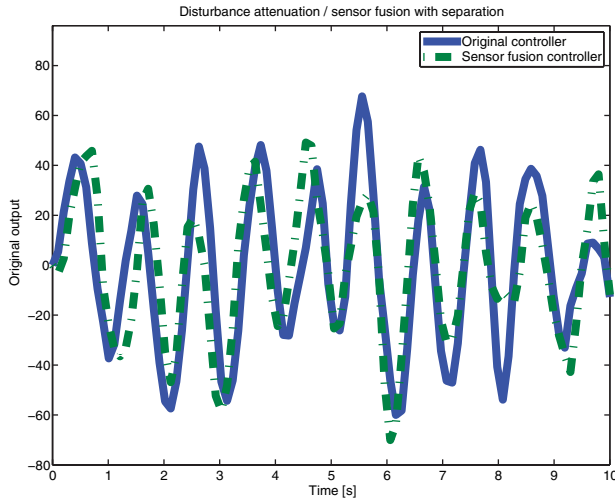
Fig. 19. Simulation of a disturbance attenuating controller using a new output based on a design with full separation. The improvement of the variance is marginal and can hardly be discerned.

Fig. 20. Simulation of a disturbance attenuating controller using a new output based on a design with partial separation only. A radical improvement of the variance is seen.

Figure 19 shows a simulation of this case, where the system is subjected to an input disturbance:

$$d = 2\sin(2\pi t) + w_1, \quad w_1 \in N(0,1)$$

and each of the measurements are subjected to independent noise sources that are normally distributed with unit variance.

It is seen from Fig. 19 that the improvement is very marginal. This discouraging result is due to two effects:

- Adding the new observer increases the phase lag of the controller
- Adding the new output also introduces more noise

It should be mentioned, however, that it is easy to come up with examples where the advantage is more obvious, e.g. in a series connected system, where a more upstream measurement is added. For random examples, though, the situation depicted here is fairly generic.

We now proceed to a design, where we deviate from the principle of full separation. Intuitively, this means that we are allowed to increase the gain of the controller, as the measurements become more reliable. Again we design a fully filtered input to the original controller, meaning that we pick $N = 0$. In this case M was found through a small optimization based on a loop transfer recovery condition. This was done by studying the loop gains from disturbance and noise, respectively, following the transients for which *uniform* improvements were obtained. As a result, the following parameter values were found:
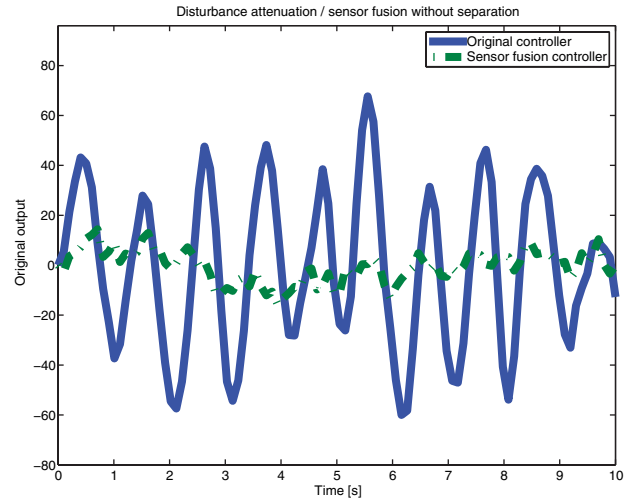
$$M = \begin{pmatrix} 2.6 & 3.4 & -1.2 \end{pmatrix}$$

A simulation result based on this design with the same inputs as in the former design case, is shown in Fig. 20.

This time, a significant performance improvement is seen. This is due in part to an improved estimate, and in part to slightly increased gains (approx. 15 %).

5. Conclusions

In this position paper it has been argued that in order to be able to apply advanced control algorithms to a number of industrial systems or processes, especially those characterized by frequent changes to the process, a new control design paradigm is required.

For most industrial systems, it is possible to come up with a control system that can stabilize the system and give a reasonable performance. As large industrial systems, however, invariably are subject to changes caused by maintenance, changed operational requirements, or improvements in instrumentation, a control system developed at a specific time based on a specific model of the system, will cease to function sooner or later, if it is not capable of re-configuring itself in the face of such changes.

In this paper, a research agenda in six distinct research tasks has been proposed which, if carried out successfully, at least to some extent would provide such a control design paradigm.

The paper only has the ambition to propose this research program, and does not attempt to give distinct answers on how to carry out the six specific research tasks outlined in the research program.

However, a few indicative results were presented. First, it was shown how new sensors could be detected and identified in closed-loop using the Hansen scheme. Identifying new components of course is a first step towards a plug & play paradigm. Next, it was demonstrated how a new controller could be added to an existing one in order to accommodate system changes, and a parameterization of such controllers were given. Finally, an approach was suggested for exploiting new measurements in an existing controller using a sensor fusion methodology.

An important ongoing research effort concerns local controller modifications in a hierarchical controller structure in response to system changes. The current research approach seems promising, and it is anticipated that results in this direction can be presented soon.

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