# Integrated Control and Diagnostics Using Robust Control Methods

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*Abstract*

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# Integrated Control and Diagnostics Using Robust Control Methods

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***Abstract*** An approach for simultaneous design of control and diagnostic modules has been studied. The method relies on robust control theory to deal with process uncertainty and addresses the problem of interaction between fault detection and control. An integrated controller/diagnostic module for a mechanical servo process has been designed. The module has been evaluated by simulation and on a physical process.

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## 1. Introduction

Growing demands on reliability and safety have increased the attention given to on-line monitoring and supervision of technical processes. A common approach when designing reliable control systems is the use of a diagnostic module for detection and isolation of system faults. When a fault is detected, the plant operator or an intelligent supervision system takes appropriate measures, *e.g.*, a reconfiguration of the control system or an emergency shutdown. The research in the area of fault detection and isolation (FDI) is performed in several research communities such as automatic control, artificial intelligence and signal processing. For recent surveys see for instance [Frank, 1990], [Isermann, 1984], [Patton, 1993].

Robustness against disturbances, process uncertainty and modeling errors is an important topic in FDI where much research is being done. However, few results make use of recent progress in the methods developed for robust control synthesis. Furthermore, the interaction between fault detection and control is usually neglected which could lead to unsatisfactory performance. A fundamental problem is here that the control and the diagnostic modules are designed independently.

In this paper an integrated approach is investigated where the control and diagnostic designs are performed simultaneously. The ideas were first presented in [Nett *et al.*, 1988] and further refined in [Tyler and Morari, 1994] and [Murad *et al.*, 1996]. In this approach, the design of the control and the diagnostic modules for an uncertain linear process is transformed into a robust performance problem. The next section gives a brief review of model-based FDI and in Section 3 the integrated design approach is presented. In Section 4 this design method is applied to a mechanical servo system and the resulting controller is tested in simulation as well as on a physical process. The design procedure is summarized and relations to other research areas are indicated in Section 5.

## 2. Model-based FDI

Industrial FDI methods often consist of limit checking of measured signals or frequency spectrum analysis. Another common approach in safety-critical control is to introduce redundancy by using several lines of identical hardware. In model-based FDI one instead makes use of the analytical redundancy inherent in the dynamic relationships between inputs and outputs of the system. A mathematical model is used to derive a residual quantity which is supposed to be "small" for an unfaulty process and "large" whenever a fault occurs. Faults could then be detected if the residual exceeds a given threshold. A number of residuals could be used, each indicating a different fault, in order to make fault isolation possible.

In Figure 1 the principle of model-based FDI is shown. The two main stages are:

- Residual generation. The inputs and the measured signals are processed in order to generate residual signals. The system that generates the residuals is often called a residual generator.
- Decision making. The residuals are examined and decision rules are applied to determine if a fault has occurred. This process may involve simple limit checking or various statistical methods.

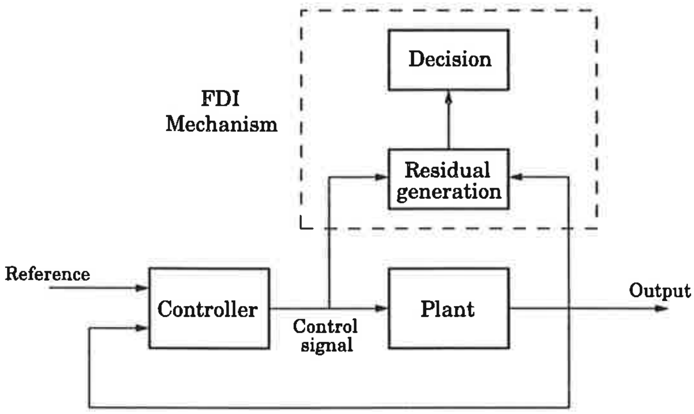


**Figure 1** The principle of model-based FDI.

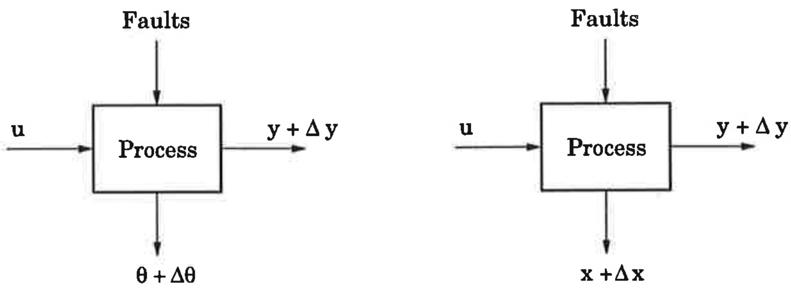


**Figure 2** Faults modeled as parameter and state perturbations for a process on state-space form, $\dot{x} = A(\theta)x + B(\theta)u, \quad y = C(\theta)x + D(\theta)u$.

A fault is something that affects the behavior of the process. This is often modeled as perturbations of the process parameters or the state variables, see Figure 2. The former could for example be used to describe increased flow resistance due to plugging or breakdown of a process component. The latter could serve as a description of sensor offset or flow leakage. There exist a number of approaches to model-based FDI. The ways of fault modeling mentioned here, give rise to the two main categories, namely

- parameter estimation methods.
- state estimation or observer-based methods.

An important issue is robustness to noise, modeling errors and process uncertainty. Lately, much efforts have been devoted to this and a number of approaches to robust residual generation have been presented, see [Patton, 1993]. However, even though most systems subject to FDI are being controlled, the interaction between the controller and the FDI module is often neglected which could lead to poor diagnostic performance as shown in [Tyler and Morari, 1994].

## 3. Integrated Control and Diagnostics

In this section the ideas of integrated control and diagnostics are introduced. The process models considered are linear with norm-bounded uncertainty. Faults are modeled as state perturbations or additive signals and the approach could thus be said to be observer-based.

A fundamental problem that is often neglected in supervision of controlled processes is that the process inputs are no longer independent of the process outputs. A diagnostic module designed for an uncontrolled plant may indeed show poor performance when used with a controlled plant. Furthermore, a diagnostic module designed for a controlled plant may still perform unsatisfactorily due to limitations imposed by the control design. To somehow motivate this we consider a typical process being controlled. The purpose of the controller is to suppress variations in the process output due to disturbances. Doing this, the controller will also suppress variations due to faults in the process and it will thus "hide" information for the diagnostic module. Note that this problem is closely related, and in some cases identical, to the "lack of excitation" problem in closed-loop identification.

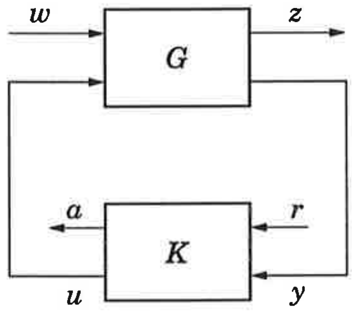


**Figure 3** 4-parameter controller connected to a plant.

To address this problem [Nett *et al.*, 1988] suggested that one should account *a priori* for the interaction between the control and the diagnostic modules by integrating their design. They introduced the 4-parameter or 4-degree-of-freedom controller. This controller has two inputs, the set-point $r$ and the plant measurement $y$, and two outputs, the control signal $u$ and an additional output $a$, and can be described by

$$\begin{bmatrix} a \\ u \end{bmatrix} = \begin{bmatrix} K_{11} & K_{12} \\ K_{21} & K_{22} \end{bmatrix} \begin{bmatrix} r \\ y \end{bmatrix}$$

The signal $a$ can be used for diagnostic purposes, for instance as a residual signal. In Figure 3 we see the 4-parameter controller connected to a general MIMO system $G$ given by

$$\begin{bmatrix} z \\ y \end{bmatrix} = \begin{bmatrix} G_{11} & G_{12} \\ G_{21} & G_{22} \end{bmatrix} \begin{bmatrix} w \\ u \end{bmatrix}$$

The inputs to $G$ are divided into uncontrolled inputs $w$ and controlled inputs $u$. The signal $w$ represents noise, disturbances and faults. The outputs are partitioned into the outputs actually used by the control algorithm, $y$, and the quantities we would like to control, $z$.

Using the 4-parameter controller, Nett *et al.* derived expressions showing tradeoffs concerning controller and diagnostic performance. In particular, for uncertain plants it was shown that control performance and diagnostic performance may have to be traded off against each other. To illustrate this we will use a simple example.

EXAMPLE 1—ADDITIVE UNCERTAINTY
Consider the closed-loop system in Figure 4. We would like the diagnostic signal $a$ to track the the input or actuator fault signal $f$ and the output $y$ to track the set-point $r$. The $\Delta$-block is an unknown transfer function representing the process uncertainty. With $K$ as before we have

$$\begin{aligned} y &= T_{yr} r + T_{yf} f \\ a &= T_{ar} r + T_{af} f \end{aligned}$$

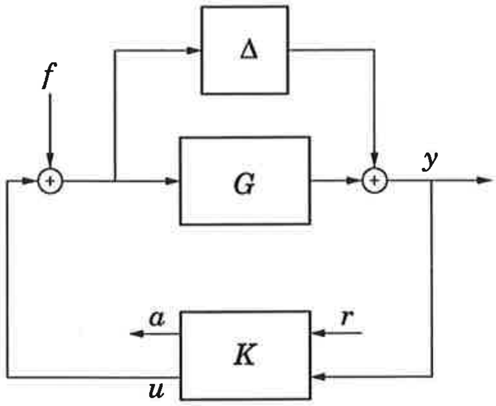


**Figure 4** 4-parameter controller connected to uncertain plant in Example 1.

where

$$
\begin{aligned}
T_{yf} &= [I - (G + \Delta)K_{22}]^{-1}(G + \Delta) \\
T_{yr} &= T_{yf}K_{21} \\
T_{af} &= K_{12}T_{yf} \\
T_{ar} &= K_{11} + K_{12}T_{yf}K_{21}
\end{aligned}
$$

In order to obtain the design objectives, $T_{yf}$ and $T_{ar}$ should be "small" while $T_{yr}$ and $T_{af}$ should be close to one. If $T_{yf}$ is designed to be small using $K_{22}$, we see that $K_{21}$ and $K_{12}$ have to be "large" to fulfill the requirements on $T_{yr}$ and $T_{af}$. For a nominal process ($\Delta = 0$) we can easily obtain $T_{ar} = 0$ using $K_{11}$. However, in the case of an uncertain plant this is not possible due to the uncertainty in $T_{yf}$. Furthermore, to make $T_{ar}$ small we would like $K_{21}$ and $K_{12}$ to be small. Thus the goal of making $T_{ar}$ small will have to be traded off against the tracking objectives. This conflict can to some extent be resolved if the control and the diagnostic objectives are separated in frequency. □

Even though the structure of the 4-parameter controller was fixed there was still a need for a systematic synthesis method giving robust performance in the case of uncertainty. In [Tyler and Morari, 1994] it was pointed out that the 4-parameter controller is a special case of the standard interconnection structure used in modern control theory. Thus, using the standard setup, robust control methods, *e.g.* $H_\infty$- and $\mu$-synthesis, can be applied to describe uncertainty and to attack the synthesis problem, see for instance [Balas *et al.*, 1993]. In Figure 5, a closed-loop system on standard form that is equivalent to that of Figure 3 is shown. In this setup all external inputs and outputs are connected to a generalized plant $\tilde{G}$ which is given by

$$
\tilde{G} = \begin{bmatrix} G_{11} & 0 & 0 & G_{12} \\ 0 & 0 & I & 0 \\ 0 & I & 0 & 0 \\ G_{21} & 0 & 0 & G_{22} \end{bmatrix}
$$

In their article, Tyler and Morari make a comparison between simultaneous and separate design of the control and the diagnostic modules. It

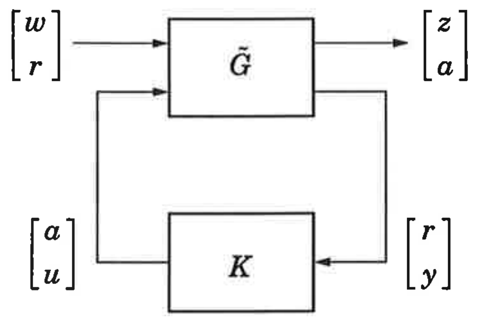


**Figure 5** Standard setup equivalent to that of figure 3.

is shown that for a plant without uncertainty, simultaneous and separate design are equivalent for a $H_2$ optimization criterion. Furthermore, for an uncertain plant using $H_\infty/\mu$-synthesis, simultaneous design gives superior diagnostic performance at the expense of inferior control performance. This clearly shows the tradeoff between control and diagnostic performances when uncertainty is present.

# 4. Design Example

We will now apply robust control methods following [Tyler and Morari, 1994] to the design of an integrated control-diagnostic module for an uncertain process. The process considered is a mechanical servo process, see [Åström and Lundh, 1992]. It is a SISO process consisting of a DC-motor, a mass and a sensor measuring the angular velocity. An additional motor makes it possible to apply a disturbance torque. The effective damping and inertia of the system can be changed through electrical feedback. A simple linear model of the nominal process is shown in Figure 7 where $k_m = 0.046$ Nm/V, $k_s = 0.1$ V/(rad/s), $d = 2.94 \cdot 10^{-4}$ Nm/(rad/s) and $J = 2.45 \cdot 10^{-3}$kg/m$^2$.

The design goal is to control the angular velocity of the servo and to detect faults in the form of disturbance torques. These goals should be

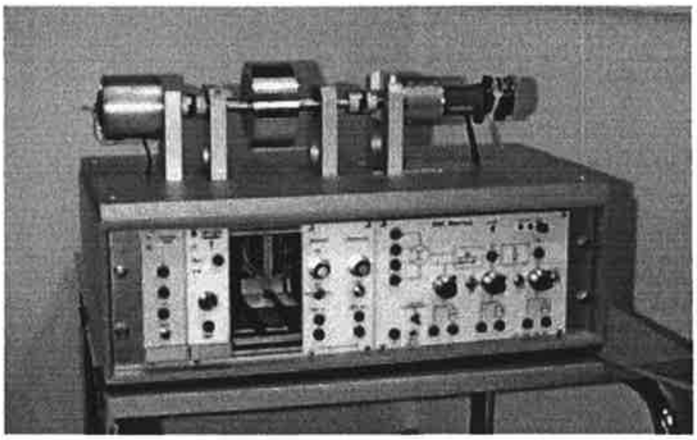

**Figure 6** The servo process.

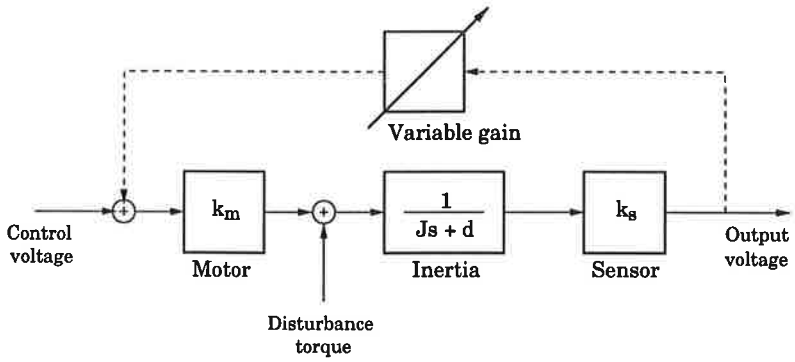


**Figure 7** Linear description of the servo process. The output voltage is proportional to the angular velocity.

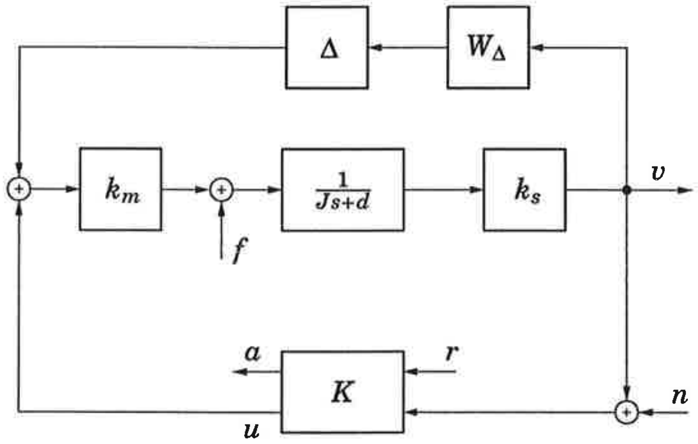


**Figure 8** The problem setup.

satisfied even though the process is not completely known. The main uncertainty is the uncertain damping coefficient due to the electrical feedback. The neglected dynamics in the motor and in the sensor are considered as less important.

The problem setup with the 4-parameter controller is shown in Figure 8. Here $\Delta$ is an unknown transfer function with $||\Delta||_\infty \leq 1$ and $W_\Delta$ is a weighting function used to represent knowledge about the uncertainty. Measurement noise is accounted for by the signal $n$ and the signal $v$ is the process output from the angular velocity sensor.

The design objectives can now be formulated as:

1. The output signal $v$ should track the reference signal $r$ and should be insensitive to noise $n$ and faults $f$.

2. The alarm signal $a$ should be large only when a fault has occurred, *i.e.*, when $f$ is large.

3. Properties 1. and 2. should hold in the presence of a bounded uncertainty $\Delta$.

Let $T_c$ be the transfer function from $[f^T, n^T, r^T]^T$ to $v - r$ and $T_d$ be the transfer function from $[f^T, n^T, r^T]^T$ to $a - f$. Note that the signal $a - f$ is the fault tracking error which could be interpreted as a residual signal.

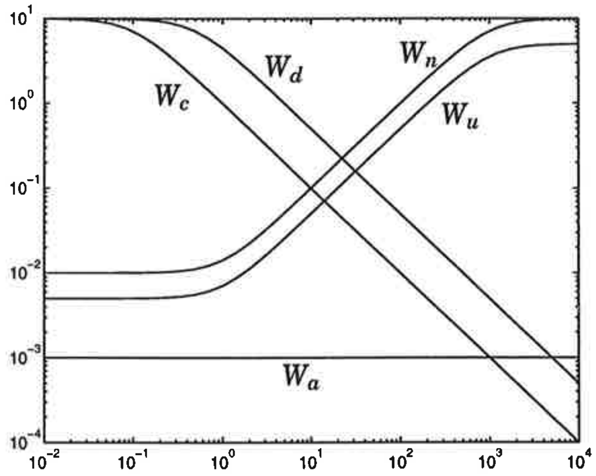


**Figure 9** Weighting functions used in the design example.

The transfer functions $T_c$ and $T_d$ are shaped using weighting functions $W_c$ and $W_d$ expressing the design objectives. In mathematical terms the design problem is stated as: Find a stabilizing $K$ such that

$$\left\| \begin{matrix} W_c T_c \\ W_d T_d \\ W_a T_a \\ W_u T_u \end{matrix} \right\| \leq 1 \quad \text{for all } \Delta \text{ satisfying } \|\Delta\|_\infty \leq 1$$

For technical reasons it is also necessary to include weights on the transfer functions to $a$ and $u$, $(T_a,\ T_u)$. In order to express further knowledge about the process and to fully exploit the freedom in the design procedure, additional weighting functions $(W_f,\ W_r,\ W_n)$ can be applied to the signals $f$, $r$ and $n$.

We assume that the damping coefficient $d$ could vary with ±50% and thus the steady-state gain and the time constant of the process vary accordingly. The weighting function $W_\Delta$ is selected to reflect the size of this parameter variation and we would like $\Delta$ to be a real parameter in the interval $[-1, 1]$. However, the current version of our design software, [Balas *et al.*, 1993], does not allow for controller synthesis with real perturbations. Instead we have to allow $\Delta$ to be a complex number with norm less than 1. This introduces extra conservatism in the design.

In Figure 9 the chosen performance weighting functions are shown. $W_c$ and $W_d$ are "large" at low frequencies expressing that we desire good control and diagnostic performance in this region. Note that in general, it is not possible to have good control and diagnostic performance in the same frequency band, see Example 1 and [Tyler and Morari, 1994]. Here, a tracking error of 10 % is accepted for both control and diagnostics. By making $W_n$ and $W_u$ "large" at high frequencies we indicate that measurement noise is likely to be present and that rapid variations in the control signal should be avoided. This is a way of reducing the bandwidth in the controller.

The solution to the design problem is obtained by rewriting the problem on standard form where the generalized plant also contains the weighting

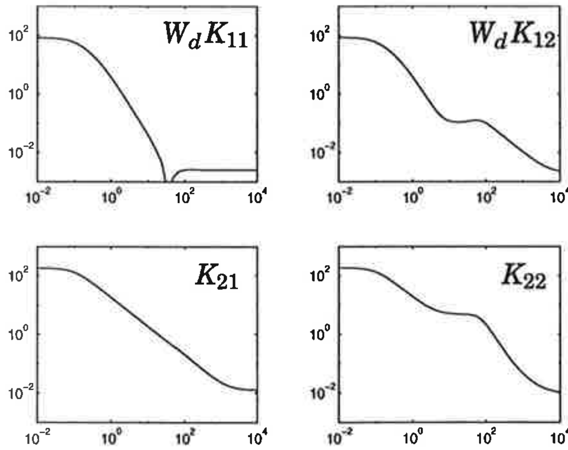


**Figure 10** Transfer functions of the reduced controller.

functions. Now the problem constitutes a 2-block $\mu$-problem which can be solved, *i.e.*, a controller $K$ can be found, using the DK-iteration method, see [Balas *et al.*, 1993].

After two iterations in the DK-iteration scheme a controller $K$ of order 15 is found giving $\mu = 1.18$. This means that the magnitude of the largest perturbation $\Delta$ allowed, while still guaranteeing the specified performance and stability, is not 1 but 1/1.18. In other words, to guarantee that our specifications are satisfied, the damping coefficient $d$ must be in the range of ±42% from the nominal value. Otherwise the performance specifications must be changed.

The diagnostic output of the controller obtained from the DK-iteration is cascaded with a filter with transfer function $W_d$. This is done in order to pick the frequency region in which we have good fault tracking. Using model reduction techniques, the controller combined with the filter is then reduced to a fourth order system thus facilitating the implementation. The transfer functions of the reduced controller are shown in Figure 10. Finally, a discrete-time version of the controller is obtained by zero order hold sampling with a sampling time of 15 ms.

The controller was first tested in simulation where the damping coefficient is 50% larger than the nominal value, see Figure 11. Noise has also been added to the measurement in order to make the simulation more realistic. Set-point tracking is good and the set-point changes is seen to have only minor effect on the filtered diagnostic signal $W_d a$. When the disturbance torque is applied after 5 seconds there is a clear response in the diagnosis signal and the effect in the process output is nicely eliminated.

After the simulation the controller was run on the real process. Through electrical feedback the damping coefficient of the process was increased approximately 50% as in the simulation. The controller was implemented in Pålsjö, a software environment for fast prototyping of real-time control systems. Pålsjö is for instance described in [Eker and Blomdell, 1996]. The results are shown in Figure 12. A disturbance torque enters the process after approximately 4 seconds. As in the simulation the controller behaves nicely and there is a clear response in the diagnosis signal when the disturbance enters.

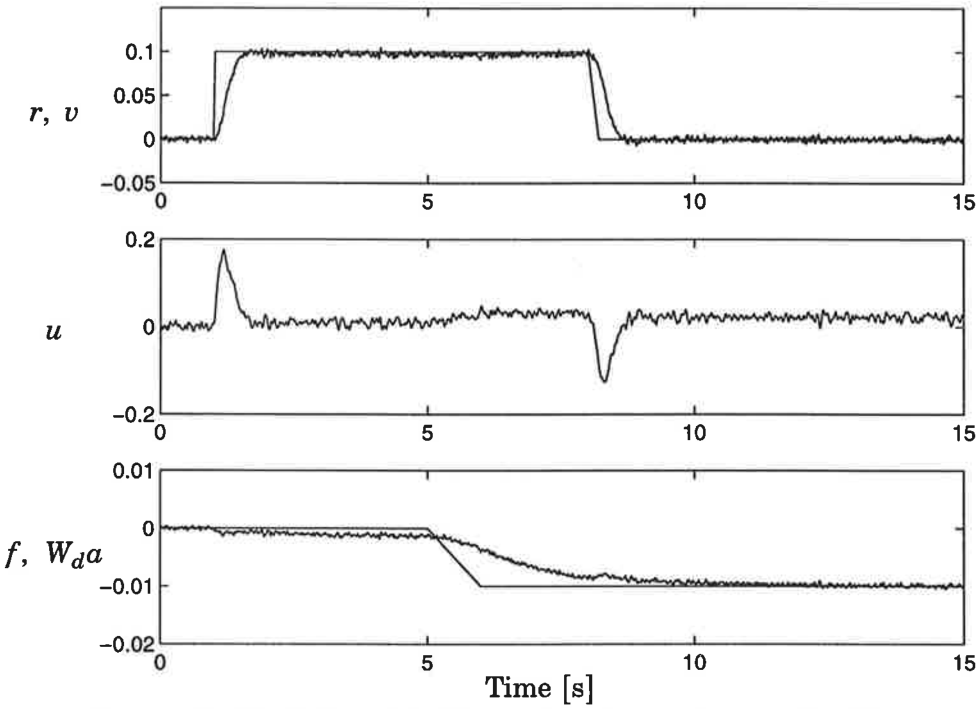


**Figure 11** Simulation of the discrete-time 4-parameter controller. The process model has a damping coefficient that is 50% larger than the nominal value. Noise has been added to the measurement signal.

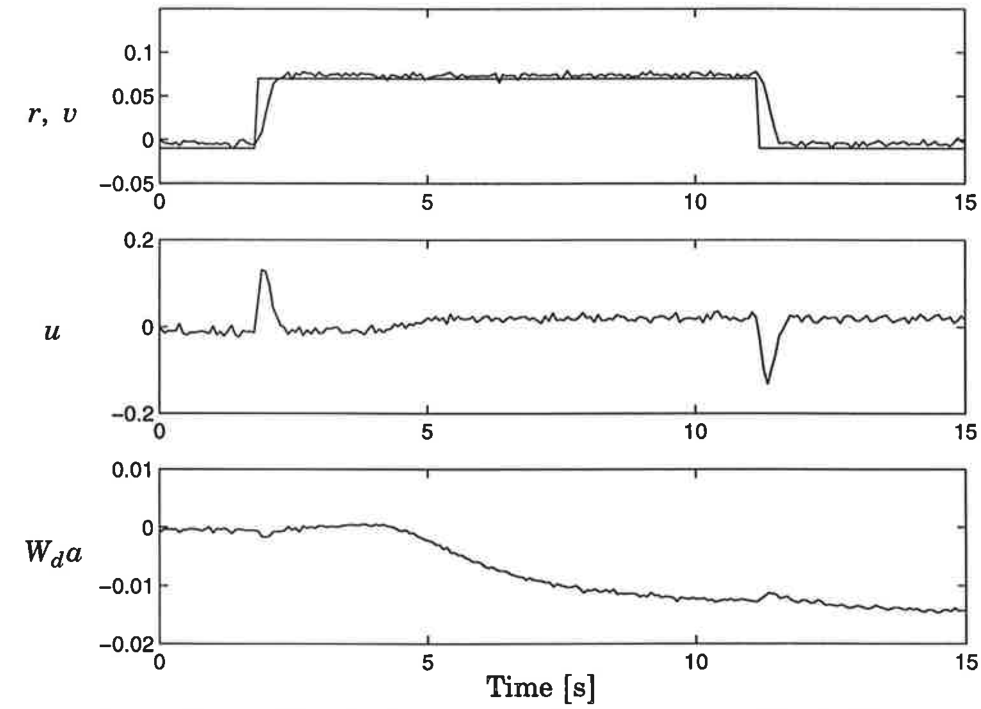


**Figure 12** Results using the real process. The damping coefficient of the process is approximately 50% larger than the nominal value.

## 5. Summary

Control and supervision systems for industrial processes are often designed independently. This may lead to unnecessarily poor diagnostic performance due to interaction between the control and the diagnostic modules, especially for uncertain plants. In general, control and diagnostic performance have to be traded off against each other. To address this problem several authors have suggested that the design of the control and the diagnostic modules should be integrated. In this paper an approach relying on robust control methods has been studied. The simultaneous design of the control and diagnostic modules is converted into a robust performance problem. This allows the designer to directly address the tradeoffs between diagnostics and control.

An integrated control/diagnostic module has been designed for a mechanical servo process showing good performance in simulation as well as on the real process. Even though a SISO process and a single fault have been considered, the method is multivariable and applies, without modification, to MIMO processes with several faults.

Norm-bounded transfer functions are used to represent *a priori* knowledge of structured or unstructured process uncertainty. This approach is sometimes criticized for giving conservative designs but as in other frameworks; the more information you have, the more you can push your design. The performance specifications are expressed using weighting functions and with these one can directly address the tradeoffs between diagnostic and control performance. However, the selection of the weighting functions can be a delicate task, especially for the user unfamiliar with the $H_\infty$-methodology.

The performance measure has been the $H_\infty$-norm. Considering that the detection algorithms processing the residuals often consist of limit checking, it would be interesting to use a peak-to-peak performance measure such as the $l_1$-norm.

Fault detection and isolation is a broad research area that has many interests in common with other disciplines. In this paper, the problem of interaction between the control and the diagnostic modules has been considered. This is closely related to the excitation problem in closed-loop identification and problems of similar nature do also arise in the area of plant-wide control. For instance, in a large plant, optimization of a single control loop may be harmful to the overall performance. Looking into other research disciplines could often give valuable insights. In [Thapliyal and Kantor, 1996], a new approach to fault detection is presented using model validation techniques. Cross-fertilization of this kind will surely contribute to the future progress of fault detection.

### Acknowledgments

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