Integrated Fault Tolerant Scheme for a DC Speed Drive

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Abstract—In this paper, an active fault tolerant control (FTC) scheme is presented with disturbance compensation. Fault-detection and compensation are merged together to propose a robust algorithm against model uncertainties. The GIMC control architecture is used as a feedback configuration for the active fault-tolerant scheme. The synthesis procedure for the parameters of the fault-tolerant scheme is carried out by using tools of robust control theory. A detection filter is designed for fault isolation taking into account uncertainties and disturbances in the mathematical model. Finally, the fault compensation strategy incorporates an estimate of the disturbances into the system to improve the performance of the closed-loop systems after the fault is detected. In order to illustrate these ideas, the speed regulation of a DC motor is selected as a case study, and experimental results are reported.

Index Terms—Fault tolerant control, robust control, $H_\infty$ design, DC motor.

I. INTRODUCTION

In many industrial applications, costly equipment is managed and human operators are involved. In these conditions, it is desirable to provide some safety degree into the automated process. Thus, the human operator must receive an indication of the possible faults into the process in order to take proper action. For certain types of faults, it is possible that the nominal control system could be designed to tolerate or maintain some of the performance for those faults (passive approach) [1]–[3]. However, this strategy tends to be conservative in the practice since the controllers have to be designed taking into account the worst-case scenario. One way of synthesizing these fault-tolerant controllers is by appealing to $H_\infty$ robust design techniques [4]–[6].

Another approach for FTC relies on the detection of a fault-case in the control process, in order to introduce a proper compensation to the feedback system (active approach) [7]. In this scheme, it is first necessary to detect a fault scenario, and next, to design an algorithm to identify the type fault occurred (fault isolation). Based on the fault isolation block, an external compensation signal for the nominal control signal is introduced, or the parameters of the controller are updated [8], [9]. Three main types of faults are recognized: actuator, sensor and plant faults [4], [10], [11]. The first two are modelled as external signals that are added to the nominal ones (additive faults). Meanwhile, the plant faults are related to mechanical wear down of the plant elements, or intrinsic changes in the dynamics of the system. These faults are usually modelled as parameter variations in the mathematical model of the plant. The problem of additive faults will be addressed in this paper.

Hence for an active FTC configuration, the first challenge is fault detection and isolation (FDI). The paradigm in FDI is to detect and isolate a fault condition despite possible disturbances, noise, and model uncertainty in the system [4], [7], [10], [11]. Thus, filters are designed such that the effect of faults is maximized at the outputs while the effect of disturbances and model uncertainty is minimized. Several approaches have been suggested: robust detection and isolation based on eigenstructure assignment [12], estimation based on $H_2$ and $H_\infty$ optimization [13], [14], detection and isolation by frequency domain optimization [15], unknown input observers [4], parity space approaches [16], robust observed-based detection [17], etc. Most of the existing research is focused on linear systems, but extensions to FDI of nonlinear systems have also been proposed in [18] and [19]. Furthermore, the applications of fuzzy logic [20] and wavelet transforms [21] to fault detection have been recently introduced.

Next, in the active approach for FTC, once the fault has been detected and isolated, the control strategy is reconfigured by a supervisory system. Recently, inspired by the Youla parameterization used in robust control theory, a reconfigurable control structure for fault compensation has been suggested in [22]. This scheme applies the GIMC (Generalized Internal Model Control) structure introduced in [23] to design a control compensation signal after a fault is detected. On the other hand, reconfigurable FTC structures have also been studied where the model-matching strategy is used to design linear controllers [24], and adaptive schemes for nonlinear systems [25]. The problem of adaptive compensation for actuator failures was recently addressed in [26]. Thus, due to the practical applications in industry processes and theoretical challenges, the research in FTC has increased in recent years, pursuing to provide certain safety degree into the automated processes.

The paper is structured as follows. Section 2 describes the problem formulation. The details about the fault detection and compensation strategies are shown in Section 3. Section 4 gives a description of the case study: speed regulation of a DC motor, and experimental results are reported. Finally, Section 5 gives some concluding remarks.
II. PROBLEM FORMULATION

A. System Description

The problem addressed in this paper is formulated as follows. Consider an LTI system $P(s)$ affected by disturbances $d \in \mathbb{R}^r$ and possible faults $f \in \mathbb{R}^d$ (additive), see Fig. 1, described by

$$
\begin{align*}
\dot{x} &= Ax + Bu + F_1f + E_1d \\
y &= Cx + Du + F_2f + E_2d
\end{align*}
$$

(1)

where $x \in \mathbb{R}^n$ represents the vector of state, $u \in \mathbb{R}^m$ the vector of input, and $y \in \mathbb{R}^p$ the vector of output. Thus, the matrix $F_1 \in \mathbb{R}^{n \times l}$ stands for the distribution matrix of the actuator faults, and $F_2 \in \mathbb{R}^{p \times l}$ for the sensor faults. Assume that a nominal controller $K(s)$ stabilizes the nominal plant and it provides a desired closed-loop performance. Consequently, the control objective of the active FTC scheme is presented as: design an integrated detection/compensation scheme such that it detects the occurrence of a fault in the closed-loop system, and provides an appropriate compensation signal $q$ to the control system in order to maintain some closed-loop performance, see Fig. 1. Two assumptions are made in the problem formulation:

- The fault is non-repetitive.
- The disturbances are known or partially known.

Remark 1: The first assumption establishes that the faults studied have a permanent effect in the system. As a result, once the fault is detected, the compensation signal $q$ is switched-on in the feedback configuration and remains active. Thus the process will have to be stopped to replace the faulty device and reset the FTC scheme. On the other hand, the information of the disturbances into the system is important to be able to provide the correct compensation signal $q$ in the FTC scheme. In case that the disturbance information could not be retrieved, the performance after the fault will be deteriorated. If there was a disturbance change at the same time of the fault, the algorithm will not be able to distinguish it immediately and the control signal will not have the correct information of the actual disturbance in the compensation. In this way, the resulting compensation after the fault will be affected. Moreover, if two or more independent faults act on the system simultaneously, the fault detection will be triggered but according with the time constant of each fault, the transient behavior will be affected after the compensation.

The open-loop system response $y$ of (1) can be analyzed in the transfer matrix form:

$$
y(s) = P_{uy}(s)u(s) + P_{fy}(s)f(s) + P_{dy}(s)d(s)
$$

(2)

where

$$
\begin{align*}
P_{uy}(s) &= C(sI - A)^{-1}B + D \\
P_{fy}(s) &= C(sI - A)^{-1}F_1 + F_2 \\
P_{dy}(s) &= C(sI - A)^{-1}E_1 + E_2
\end{align*}
$$

(3)

Hence $P_{uy}(s)$ represents the nominal plant (mapping from $u$ to $y$). Furthermore assume that there exists knowledge about the model uncertainties in the description of the nominal plant [6]. Two possible scenarios can be seen: structured or unstructured uncertainty according with robust control theory.

- If the uncertainty can be derived from certain parameters of the model, where a range of variation can be deduced, then a structured uncertainty is adopted. As a consequence, the real plant can be represented by an upper linear fractional transformation (LFT):

$$
\tilde{P}_{uy}(s) = F_u(P, \Delta) = \tilde{P}_{22} + \tilde{P}_{21}\Delta(I - \tilde{P}_{11}\Delta)^{-1}\tilde{P}_{12}
$$

(4)

where

$$
\Delta = \text{diag}[\delta_1 \delta_2 \ldots \delta_k] \quad \text{with} \quad \delta_i \in (-1, 1) \quad i = 1, \ldots, k
$$

and the index $k$ represents the number of uncertain parameters. In this case, the generalized plant $P$ is derived by pulling out the variation parameters $\delta_i$ from the nominal plant. Note that for the nominal plant $P_{uy}(s) = \tilde{P}_{22}(s)$.

- In the case that the uncertainty could be considered unstructured, the real plant $P_{uy}$ is given by

$$
\tilde{P}_{uy}(s) = P_{uy}(s) + W_2(s)\Delta(s)W_1(s) = F_u(P, \Delta)
$$

(5)

where $W_1, W_2 \in RH_{\infty}$ are weighting functions for the uncertainty, $\Delta \in RH_{\infty}$ with $||\Delta||_{\infty} < 1$, and in this specific case, the generalized plant $P$ is given by

$$
P = \begin{bmatrix}
0 & W_2 \\
W_1 & P_{uy}
\end{bmatrix}
$$

(6)

B. Residual Design

In FDI theory, based on the input-output description of the system, a signal that contains information of faults has to be designed: residual [4], [10], [11]. Using the representation (1), the nominal plant can be expressed by a left coprime factorization, i.e. $P_{uy}(s) = M^{-1}(s)\tilde{N}(s)$ where $\tilde{N}, M \in RH_{\infty}$. Then a residual signal $r$ can be constructed by:

$$
r(s) = H(s)[-\tilde{N}(s)u(s) + \tilde{M}(s)y(s)]
$$

(7)

where $H \in RH_{\infty}$ is known as detection filter. By substituting (2) and using the model uncertainty description, it is obtained that

$$
r(s) = H(s)[\tilde{M}(s)\Delta_{uy}(s)u(s) + \tilde{N}_d(s)d(s) + \tilde{N}_f(s)f(s)]
$$

(8)
where \( \Delta_{uy} = W_2(s)\Delta(s)W_1(s) \) or \( \Delta_{uy} = P_{21}\Delta(I - P_{11}\Delta)^{-1}P_{12} \) for unstructured and structured uncertainty respectively. Moreover, using the problem formulation in (1), then
\[
P_{fy}(s) = \bar{M}^{-1}(s)\hat{N}_f(s), \quad P_{dy}(s) = \bar{M}^{-1}(s)\hat{N}_d(s) \tag{10}
\]
with \( \hat{N}_d, \hat{N}_f \in RH_{\infty} \). As a consequence, the residual signal \( r \) is affected by the control signal through the model uncertainty, the disturbances and the faults. Therefore, the aim of the filter \( H(s) \) must be to isolate the effect of faults \( f \) in the residual \( r \), i.e.

- \( H(s)\bar{M}(s)\Delta_{uy}(s) \approx 0 \) and \( H(s)\hat{N}_d(s) \approx 0 \),
- \( H(s)\hat{N}_f(s) \neq 0 \) and as large as possible in some sense.

For perfect fault isolation, it is then needed \( H(s)\hat{N}_f(s) \approx I \). In order to detect a fault-scenario, the following residual evaluation criteria are commonly followed
\[
\|r\| = \|r\|_{2,T} = \sqrt{\int_{t-T}^{t} r^*(\tau)r(\tau)d\tau} \tag{11}
\]
\[
\|r\| = \|r\|_{\infty} = \sup_{t} \|r\|_2 \tag{12}
\]
where \( T \) is the window length or horizon of evaluation. In some special cases, the filter \( H(s) \) can cancel completely the effect of uncertainty and disturbances in the residual. Therefore, in the practice to prevent a false alarm in the evaluation, a threshold value \( J_{th} \) is selected such that
\[
J_{th} = \sup_{f=0,\forall d,u} \|r\| \tag{13}
\]
The threshold \( J_{th} \), in general, can be also a function of time [4]. However, this approach is not pursued in this paper. Once the residual signal is constructed, a fault can then be detected according to the criterion:
\[
\|r\| \geq J_{th} \tag{14}
\]
where the threshold for detection can be calculated by using the size of the uncertainty, the disturbance information and the maximum value of the control signal. Thus, by applying the triangle inequality to (9)
\[
\|r\| \leq \left\| H(s) \left[ \bar{M}(s)\Delta_{uy}(s) \quad \hat{N}_d(s) \right] \right\| \begin{bmatrix} u \\ d \end{bmatrix} + \|H(s)\hat{N}_f(s)\| ||f||. \tag{15}
\]
a threshold \( J_{th} \) can be chosen, where the relation between the \( L_1 \) norm of systems and the \( l_{\infty} \) norm of signals [27] can be exploited, i.e.
\[
J_{th} = \left\| H(s) \left[ \bar{M}(s)\Delta_{uy}(s) \quad \hat{N}_d(s) \right] \right\|_1 \begin{bmatrix} u \\ d \end{bmatrix} \right\|_{\infty} \tag{16}
\]
Alternatively, the relation between the \( H_{\infty} \) norm of systems and the \( l_2 \) norm of signals could be used instead [4], [6]. However, the threshold using the \( L_1 \) norm tend to be more appropriate, since the signals in the feedback loop are in general bounded in time. Moreover, the \( l_2 \) norm has to be approximated using a finite window length, which adds conservativeness to this type of bound. As a result, define the set of strongly detectable faults
\[
\Upsilon = \left\{ f | \inf_{\forall d,u} \|r\| \geq J_{th} \right\} \tag{17}
\]
Consequently, the optimal filter \( H(s) \) must maximize the size of \( \Upsilon \) [17], i.e.
\[
\max_{H(s) \in RH_{\infty}} \dim \Upsilon \tag{18}
\]
in order to obtain the best tradeoff between fault sensitivity and robustness.

### III. Fault-Tolerant Scheme

In this section, the active FTC strategy is described in detail.

#### A. Generalized Internal Model Control

The FTC architecture proposed in this work is derived from robust control theory [6], where a new implementation of the Youla parameterization called Generalized Internal Model Control (GIMC) is used [22], [23], see Fig. 2. In this configuration, the nominal controller \( \bar{K}(s) \) is represented by its left coprime factorization, i.e. \( \bar{K}(s) = V^{-1}(s)\bar{U}(s) \) such that \( \bar{U}, V \in RH_{\infty} \). It is observed that \( f_e \) represents the filtered error between the estimated output and the true output of the system. Thus if \( f_e = 0 (\Rightarrow q = 0) \) that will represent that there is no model uncertainties, external disturbances or faults into the system, then the feedback system will be solely controlled by the nominal controller \( K(s) \). Consequently, from the GIMC configuration in Fig. 2, the control signal \( u \) has a component due to the control tracking error and will have another from the filtered error \( f_e \) through the compensator \( Q \) in the fault-scenario:
\[
u(s) = V^{-1}(s)\left[\bar{U}(se(s) + q(s))\right] = V^{-1}(s)\left[\bar{U}(s)\{ref(s) - y(s)\} + Qf_e(s)\right] \tag{19}
\]
Note that if disturbances \( d \) are affecting the nominal system then the filtered error \( f_e \) will be drastically altered. However, it is assumed that the disturbance \( d \) is known or partially known. Therefore, this information can be feedforward into the estimation process to cancel its effect from the filtered error \( f_e \). As a consequence, a new implementation of the GIMC architecture is suggested in Fig. 3. The residual signal proposed in the previous section, see (8), can be constructed by taking the signal \( f_e \) and process it through the detection filter
where \( T_{e_f \nu} = \mathcal{F}_l(F_u(G_{\mathcal{H}}, \Delta), H) \) with
\[
\begin{bmatrix}
  z \\
  e_f \\
  f_e
\end{bmatrix}
= \begin{bmatrix}
  \mathcal{P}_{11} & 0 & 0 \\
  0 & -I & 0 \\
  \bar{M}\mathcal{P}_{21} & \bar{N}_f & \bar{N}_d & \bar{M}\mathcal{P}_{22} & -\bar{N} & 0
\end{bmatrix}
\begin{bmatrix}
  w \\
  f \\
  d \\
  u \\
  r
\end{bmatrix}
\]

the true plant is given by \( \bar{P}_{uy} = \mathcal{F}_u(\mathcal{P}, \Delta) \) according with the uncertainty representations of (4) and (6), \( \nu = [f \ d \ u]^T \) is the vector of inputs, and \( G_{\mathcal{H}} \) the generalized plant in the LFT format. The design problem in (20) can be tackled with tools from robust control theory (\( \mu \)-synthesis) [6]. The synthesis procedure using \( \mu \)-synthesis is carried out in an iterative algorithm that performs a two-parameter minimization in sequential fashion to reach the optimal solution: \( D - K \) iteration [6].

C. Fault Compensation

In the design of the fault compensation signal \( q \), the transfer matrix \( Q(s) \) is chosen to maintain stability against any fault. Thus, the problem of robust stabilization is addressed. However, some performance specification could also be incorporated in the design of \( Q(s) \). If there exist \( K_i(s) \) controllers that have a desired performance against certain type of faults \( f_i \), different from the nominal controller \( \hat{K} = \hat{V}^{-1}\hat{U} \), then the architecture GIMC allows to design specific compensators for each one \( Q_i(s) \), according with the relation:
\[
Q_i(s) = \hat{V}(s) [K_i(s) - K(s)] \left[ \hat{N}(s)K_i(s) + \hat{M}(s) \right]^{-1}
\]
for the nominal plant \( P_{uy}(s) = \hat{M}^{-1}(s)\hat{N}(s) \). This approach will be pursued in future work.

Only one limitation on the transfer matrix \( Q(s) \) has to be considered, according with the Youla parameterization, it
has to be stable, i.e. \( Q \in RH_\infty \). The synthesis process is again carried out through the philosophy of robust control. In general, the sensor and actuator faults can be modelled in a multiplicative form
\[
\begin{align*}
\tilde{y}(s) &= [I + \Delta_s]y(s) \\
\tilde{u}(s) &= [I + \Delta_a]u(s)
\end{align*}
\]
where \( \Delta_s, \Delta_a \in RH_\infty \) represent the sensor and actuator perturbations due to the faults [22]. Consequently, if these terms are appended to the nominal plant \( P_{uy}(s) \), then the faulted input-output mapping \( \tilde{P}_{uy}(s) \) can be represented as
\[
\begin{align*}
\tilde{P}_{uy}(s) &= P_{uy}(s)[I + \Delta_a] \quad \text{(actuator fault)} \\
\tilde{P}_{uy}(s) &= [I + \Delta_s]P_{uy}(s) \quad \text{(sensor fault)}
\end{align*}
\]
Thus the sensor or actuator faults can be modelled as output or input model uncertainties respectively. As mentioned before, we shall consider a basic robustness requirement in this paper, i.e. the closed-loop stability. Hence our objective is to design \( Q(s) \) to maximize the failure tolerance in the closed-loop system, i.e.
\[
\min_{Q(s) \in RH_\infty} \|T_{zw}\|_\infty
\]
where \( T_{zw} \) is the closed-loop transfer function from signals \( w \) to \( z \). Two design scenarios can be presented according with the stability of the nominal plant \( P_{uy}(s) \) [22]:
\begin{enumerate}
\item \( P_{uy} \in RH_\infty \Rightarrow \) the optimal compensator is given by \( Q(s) = -\tilde{U}(s)\tilde{M}^{-1}(s) \), for any plant and type of uncertainty description [22]. Recall that \( \tilde{U}(s) \) and \( \tilde{M}(s) \) are related to the coprime factorizations of the nominal controller \( K(s) \) and plant \( P_{uy}(s) \).
\item \( P_{uy} \notin RH_\infty \Rightarrow \) a weighted \( H_\infty \) approximation has to be solved. For this purpose, the synthesis problem can be put into an LFT framework. Hence, \( Q(s) \) is chosen according to
\end{enumerate}
\[
\gamma = \min_{Q(s) \in RH_\infty} \|F_I(G_Q, Q)\|_\infty
\]
and internal stability is guaranteed if \( \|\Delta\|_\infty < 1/\gamma \). If an output uncertainty (sensor fault) is considered (i.e. \( \tilde{P}_{uy} = [I + \Delta_s]P_{uy} \)), the generalized plant \( G_Q \) will be given by
\[
G_Q = \begin{bmatrix}
-\tilde{S}(s)P_{uy}(s)K(s) & \tilde{S}(s)P_{uy}(s)\tilde{V}^{-1}(s) \\
\tilde{M}(s) & 0
\end{bmatrix}
\]
where \( \tilde{S}(s) = [I + P_{uy}(s)K(s)]^{-1} \). Note that in this case \( \gamma \geq 1 \) since this will represent that the maximum tolerable uncertainty is always \( \|\Delta_s\|_\infty < 1 \). Otherwise, the uncertainty could take the value \( \Delta_s = -I \) (sensors outage) and the closed-loop will become unstable.

In an alternative way, the optimal \( Q(s) \) can be derived by following the problem formulation presented in (1) and (3), and considering the setup of Fig. 5. This applies only to the case \( P_{uy} \in RH_\infty \Rightarrow \tilde{M}^{-1} \in RH_\infty \).

**Theorem 1:** Suppose \( P_{uy} \in RH_\infty \) and \( K(s) = \tilde{V}^{-1}(s)\tilde{U}(s) \) is a stabilizing controller of the nominal plant \( P_{uy}(s) \) that satisfies the closed-loop performance requirements, then
\[
Q(s) = -\tilde{U}(s)\tilde{M}^{-1}(s)
\]
is the optimal solution that decouples the fault \( f \) signal from the control signal \( u \). Moreover, if \( Q(s) \) is chosen in this way, and the compensation scheme of Fig. 5 is implemented after the fault is detected, then the control signal \( u \) will have contributions from the disturbance \( d \) and reference \( ref \):
\[
u(s) = [I + K(s)P_{uy}(s)]^{-1}[-K(s)P_{dy}(s)d(s) + K(s)ref(s)]
\]

![General Fault Compensation Setup](image)

**Proof:** From Fig. 5, it can be seen that
\[
u(s) = \tilde{V}^{-1}(s) \left\{ \tilde{N}(s)u(s) + \tilde{N}_d(s)d(s) - \tilde{M}(s)(\text{ref}(s) - y(s)) \right\}
\]
and by substituting (3) and (10) in the previous equation, it is obtained after simplification
\[
u(s) = \tilde{V}^{-1}(s) \left\{ Q(s)\tilde{M} + \tilde{U}(s) \right\} P_{fu}(s)f(s) - \tilde{U}(s)\left\{ P_{uy}(s)u(s) - P_{dy}(s)d(s) + \text{ref}(s) \right\}
\]
Therefore, to decouple the fault signal \( f \) from the control signal \( u \) is needed
\[
Q(s)\tilde{M} + \tilde{U}(s) = 0 \implies Q = -\tilde{U}(s)\tilde{M}^{-1}(s)
\]
Note that since \( \tilde{M}^{-1} \in RH_\infty \), then \( Q \in RH_\infty \). Finally, by substitution of \( Q(s) \) into the control signal \( u \) in (30), it is obtained (28).

**Remark 2:** From the proof of the previous theorem, it is important to mention that if the disturbance information \( d \) is not feedforward into the fault-tolerant scheme, then the control signal \( u \) will not adjust its value according the disturbance. Hence, the tracking performance of the resulting closed-loop system will be largely affected, but the closed-loop stability is always guaranteed since the nominal controller internally stabilizes the nominal plant [23], and the disturbances are additive in the loop.
Remark 3: It is common that some types of faults are more easy to detect than others, for example abrupt and incipient
[11]. In the case of the abrupt faults, the detection time is almost instantaneous, since a large peak is observed in the residual. On the other hand, for an incipient fault, it is more difficult to detect its presence in the residual. Thus, it is possible to have a delay in the detection of the fault triggering or could not be detected at all. Furthermore, in the presence of control constraints as saturation, it is possible that the system could not be stabilized if there is a significant delay in the detection process, since the system could enter in the nonlinear part of the saturation. This delay is argued to be a factor of the speed of response of the nominal controller, as it was seen in simulation. Hence, if the controller has fast dynamics, the tolerable delay is reduced.

IV. CASE STUDY: SPEED REGULATION OF A DC MOTOR

To illustrate the mentioned FTC technique, the application to a dc-motor speed drive is presented next [28]. The test-bed setup is shown in Fig. 6, and it consists of a 1 HP dc-motor connected to a 3/4 HP permanent magnet motor. The latter one acts as a generator in order to provide a load to the shunt dc-motor. In this setup, the load torque varies according with the control signal $u$. In the implementation, there are measurements of electrical currents made by Hall-effect sensors, and angular velocity by a tacogenerator of 50V/1000 RPM with ±5% tolerance.

![Test-bed Setup](image)

Fig. 6. Test-bed Setup.

A. Model Description

The dc-motor is considered in a separated excitation configuration. Thus, the field (stator) voltage $v_f$ is fixed to a constant value, and the armature (rotor) voltage $v_a$ is varied in order to control the angular velocity $\omega$ of the motor. Consequently, the electromagnetic field provided by stator is held constant. Two measurements are available for feedback purposes: armature current $i_a$ and angular velocity $\omega$. Thus, the dc-motor is modelled as a system with one-input ($v_a$) and two-outputs ($i_a$ and $\omega$):

$$\frac{di_a}{dt} = -\frac{R_a}{L_a}i_a - \frac{K_b}{L_a}\omega + \frac{1}{L_a}v_a$$

$$\frac{d\omega}{dt} = \frac{K_b}{J}i_a - \frac{B}{J}\omega - \frac{1}{J}T_l\tag{32}$$

where the parameters of the dc-motor were obtained through a systematic experimental process [28], and they are shown in Table I. In the motor description, the load torque $T_l$ is represented as a disturbance into the system, however this variable cannot be measured in real-time. Nevertheless, during the experiments, it is assumed to behave as a constant or present a very slow variation. In this way, its steady state value can be calculated from the angular velocity and armature current measurements by the relation:

$$T_l = K_b i_a - B \omega \tag{33}$$

The armature voltage $v_a$ is controlled by dc-dc chopper working under a PWM scheme (switching frequency 50kHz), where the control parameter is the duty cycle. The chopper was selected as control actuator due to its fast response and linear dynamics. The construction of the actuator was carried out in our lab, and it is designed such that it is controlled by a voltage signal $u$ in the interval $[0, 5V]$. This saturation in the control signal $u$ did not limited the performance of the system, due to the fast dynamics of the actuator related to the time constant of the dc-motor. The control actuator (dc-dc chopper) was modelled as a first order system:

$$G_a(s) = \frac{v_a(s)}{u(s)} = K_a \frac{s + a}{s + b} \tag{34}$$

where the parameters of the model ($K_a, a, b$) were obtained experimentally by applying the theory of algebraic identification [29], [30].

Six different experiments were carried out and the average values of the parameters $K_a, a$ and $b$ are given in Table II. In the overall mathematical model, there exist some uncertainty in the description of some of the parameters including motor and actuator. Thus, for $R_a, L_a, J, K_a, a$ and $b$, they can be
TABLE II
CONTROL ACTUATOR PARAMETERS.

| $K_a$ = 20.71 | Actuator Gain |
| $a$ = −6.66 | zero location |
| $b$ = 5.43  | pole location |

associated with a parametric uncertainty description:

$$\dot{\hat{\beta}} = \hat{\beta}(1 + 0.7\delta_R)$$

$$\hat{L}_0 = L_0(1 + 0.2\delta_L)$$

$$\hat{j} = j(1 + 0.1\delta_j)$$

$$\hat{K}_a = K_a(1 + 0.015\delta_K)$$

$$\dot{\hat{a}} = a(1 + 0.09\delta_a)$$

$$\dot{\hat{b}} = b(1 + 0.23\delta_b)$$

(35)

where “•” denotes the real value of the variables, and $-1 \leq \delta_i \leq 1$. As a consequence, a structured uncertainty description can be arranged for the open-loop system. This uncertainty description will be used to design the fault detection filter $H(s)$.

B. Design of Fault Tolerant Scheme

Note that with the parameters given to the nominal plant (32) and actuator (34), the open-loop system is stable. Next, the nominal controller $K(s)$ is designed to guarantee good step tracking capabilities. For this purpose, an LQG controller [6] is synthesized where integral action is appended to the controller to improve closed-loop tracking and disturbance rejection.

Using a structured uncertainty description for the plant, the optimization problem formulated in (20) was carried out to design $H(s)$. Thus, according with the diagram of Fig. 4, the LFT is constructed to formulate the robust performance filter problem using μ-synthesis. The $D - K$ iteration was run and the resulting filter of order 21th was reduced through balance truncation to 9th. Finally, since the nominal plant is stable, then the compensation controller is selected $Q(s) = -\hat{U}(s)M^{-1}(s)$.

C. Experimental Implementation

Next, the integrated FTC structure shown in Fig. 3 was implemented first in simulation by using MATLAB/Simulink®, and experimentally in the dSpace system. The disturbance estimation $\hat{T}_i$ in (33) was used to feedforward this information into the active FTC scheme. Two abrupt faults were considered for the sensors:

1) Case 1: the angular velocity sensor $\omega$ is completely disconnected from the system at a given time,

2) Case 2: there is an outage of the armature current $i_a$ sensor.

The failure cases were simulated by software in the system and not directly in the experiment. In both scenarios, the fault-tolerant system was able to compensate properly the control signal for these faults. The experimental results for the tacogenerator fault are shown in Fig. 7. Note that in the case of angular velocity fault, the uncompensated closed-loop system becomes unstable. Since, after the fault, the controller detects a sudden drop in the angular velocity measurement and due to its integral action, the nominal control signal starts to grow looking to increase the armature voltage in order to compensate the velocity. Therefore, without the compensation, the control signal will keep increasing due to the erroneous information of the velocity sensor. This behavior will be present when the nominal controllers contain integral action, as in PI and PID compensators, which are a common choice in industrial processes. As a result, the control compensation is necessary in these cases to avoid damage to the motor or accidents in the process. The angular velocity reference for both fault cases was set to 1500 RPM. The plots illustrate that the compensation is capable to reconfigure the control strategy to maintain some of the closed-loop performance. However, it is noticeable that the reference is not maintained, this is due to the estimation of the load torque $T_l$ (disturbance) which is an approximation of the real value. As a consequence, the error in the estimation of the load torque affects the tracking capabilities of the overall system. Therefore, if this signal could be acquired by a direct measurement then the compensation will be more accurate. This behavior was seen during simulation. Now, in Fig. 8, the experimental testing for a change of reference after a fault scenario (Case 1) is illustrated. This plot shows that the system still is able to follow a reference signal after the fault, but with a certain error.

In order to investigate further the performance of the FTC scheme, an exponential type of fault was tested experimentally. Thus, the angular velocity fault was modelled as an exponential drop in the sensor gain, with the following characteristics:

$$\dot{\omega} = \left\{ \begin{array}{ll}
\omega & t < t_{on} \\
\omega \left[ 1 - 0.5 \left( 1 - e^{-15(t - t_{on})} \right) \right] & t \geq t_{on}
\end{array} \right. \quad (36)$$

where $t_{on}$ is the activation time of the fault, and $\dot{\omega}$ denotes the angular velocity measurement by the sensor, and $\omega$ its real value. The system response is shown in Fig. 9. Hence the system without compensation is unstable and the compensated system still is able to recover stability, but the reference tracking performance is deteriorated.

Remark 4: An slower incipient type of fault, compared to (36), was also tested in simulation. Thus, the sensor measurement was slowly decaying after the triggering time. For this type of fault, the main problem is fault detection, since according to the decaying rate of the measurement, the residual will take more or less time to overcome the detection threshold. However, the FTC algorithm can also compensate this fault, but there is some deterioration of the performance due to the delay time in the detection process. The implementation for this fault was only carried out in simulation, since there was a risk of damaging the dc-motor in the actual test-bed setup. Consequently, other decision algorithms have to be applied to improve the size of the set of strongly detectable faults $\mathcal{Y}$, for example based on wavelet analysis and fuzzy logic.
An integrated active FTC scheme was introduced. The strategy relies on information of the process and potential uncertainties. The GIMC control architecture is used as a feedback configuration for the fault-tolerant scheme. The synthesis procedures were carried out by using robust control theory. The disturbances entering the system affect the performance of the compensated control system, consequently this information is estimated and feedback into the FTC architecture to cancel their effect. The speed regulation of a dc motor was selected as a case study, and the experimental results show success in the detection and compensation for the fault scenarios tested. However, the fault detection/decision scheme limits the overall performance of the FTC strategy, and more advanced techniques should be explored in future work. In summary, from the results obtained in the paper, it is observed that the area of FTC presents challenging theoretical problems:

- Robust disturbance decoupling,
- Detection of incipient faults,
- Delay in fault detection and compensation,
- Fault Compensation with performance specifications

that have to be addressed for advanced practical applications.

**ACKNOWLEDGMENT**

The authors would like to thank the anonymous reviewers for helping to improve the quality of the paper.

**REFERENCES**


