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Robust FDI for FTC Coordination in a Distributed Network System

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Abstract: This paper focuses on the development of a suitable Fault Detection and Isolation (FDI) strategy for application to a system of inter-connected and distributed systems, as a basis for a fault-tolerant Network Control System (NCS) problem. The work follows a recent study showing that a hierarchical decentralized control system architecture may be suitable for fault-tolerant control (FTC) of a network of distributed and interacting subsystems. The main idea is to use robust FDI methods to facilitate the discrimination between faults acting within one subsystem and faults acting in other areas of the network, so that a powerful form of active FTC of the NCS can be implemented, through an autonomous network coordinator. By using a robust form of the Unknown Input Observer (UIO), fault effects in each subsystem are de-coupled from the other subsystems, thus facilitating a powerful way to achieve local FDI in each subsystem under autonomous system coordination. Whilst the autonomous distributed control system provides active FTC under learning control, the FDI-based Reconfiguration Task enhances the network fault-tolerance, so that more significant subsystem faults can be accommodated in order to achieve a suitable standard of Quality of Performance (QoP) of the NCS.

1. INTRODUCTION

The NCS concept began to draw the attention of academic researchers in the 1990s due to amazing advantages of flexibility, reconfigurability, etc. Recently, a considerable volume of theoretical tools have emerged which now extends to encompass FTC approaches to NCS (Ding *et al*., 2004).

Traditionally, large inter-connected systems have been viewed within a distributed, over-lapping or large-scale systems framework (Singh *et al*, 1978). A number of tools for Control, FTC and FDI have been developed that can be applied to NCS if due care is given to the distributed system structure in terms of inter-connections, over-lapping decompositions and redundancy (Singh *et al*, 1983; Chen & Stankovi, 2005). The complexity arises partly from the data communications (which were not present in the study of large-scale systems), and the need to identify *two* different sets of faults namely in (a) the physical system and (b) in the network, and their interactions. The NCS is itself a complex and uncertain system for which all Control operations must be reliable, secure and fault-tolerant. To achieve good QoP and Quality of Service (QoS) we need to ensure that the NCS is fault-tolerant, based on redundancy concepts and FDI. The FDI should be used to determine the severity of a fault and whether or not a reconfiguration of the network is required. This paper uses the distributed control systems concept (Patton *et al*, 2007), focusing on architectures that can be used to achieve good FTC performance, even under autonomous system operation (Kambhampati *et al,* 1996). Bearing in mind the need to achieve FTC in NCS the following goals must be achieved:

(a) A deeper understanding of FTC in the context of a distributed networked control problem.

(b) The development of suitable robust FDI strategies based on concepts which relate to the inter-connected nature of the NCS.

Robustness in FDI (Chen & Patton, 1999) must be addressed whenever a model-based method is used. For the complex and inter-connected NCS this is no exception and robust FDI is necessary. We use the unknown input observer/estimator in a new way, applied to each NCS subsystem and by decoupling the estimated subsystem interactions, thereby enhance the robustness in FDI for the network. The robust FDI residuals facilitate a mechanism for reconfigurable FTC.

Section 2 outlines the NCS structure as a network of inter-connected subsystems along with the hierarchical and distributed architecture chosen to provide fault-tolerance under autonomous co-ordination. Section 3 outlines the robust FDI principles, using the UIO FDI scheme (Patton *et al*, 1989; Chen *et al,* 1996) to achieve robust de-coupling of subsystem interconnection faults. Section 4 outlines a benchmark study example of a distributed 3-Tank system. Results are given to demonstrate the performance of the robust FDI within the autonomous NCS scheme, demonstrating good FTC performance for different fault levels. Section 5 gives the concluding remarks.

2. NCS PROBLEM STATEMENT

The Control aspects of NCS can be formulated as a system of inter-connected subsystems. In this way the goals outlined above can be investigated. The NCS is assumed to comprise wired connections so that the communications network has effectively infinite bandwidth. This assumption means that the Control and FDI problems (concerned with control) can remain within the Control Network Description (Patton *et al*, 2007) and single-rate sampling is sufficient. This means that the problem description can be given in continuous time.

2.1 N Interconnected Subsystems

Each subsystem of this NCS (Fig. 1) can be described by the following general and non-linear dynamic representation of N inter-connected subsystems (Patton *et al*, 2007):

$$\dot{x}_i = F_i(x_i, z_i, u_i) = f_i(x_i, u_i) + G_i(z_i) \tag{1}$$

where: $(x_i, z_i, u_i) \to F_i(x_i, z_i, u_i) : \Re^{n_i} \times \Re^{l_i} \times \Re^{m_i} \to \Re^{n_i}$, x_i, z_i and u_i are the states, inter-connections and the inputs of the i^{th} subsystem component, $i = 1,2,\ldots,N$. Furthermore, $(x_i, u_i) \to f_i(x_i, u_i) : \Re^{n_i} \times \Re^{m_i} \to \Re^{n_i}$ is a local (or isolated system) model of the i^{th} component, and $(z_i) \to G_i(z_i) : \Re^{l_i} \to \Re^{l_i}$ are the non-linear inter-connection mappings involving the subsystem connections. The $i = 1,2,\ldots, N$ interconnection states are(Patton *et al* (2007):

$$z_i = \sum_{j=1}^{N} H_j^i x_j \quad \mathrm{i=1,2,\ldots,N} \tag{2}$$

The H_j^i are $\Re^i \times \Re^j$ matrices describing the interconnections between the subsystems. The subsystem control performances are measured, based on linearised subsystem models, via local cost functions: $J_i(x_i, t; u_i)$, $i = 1,2\ldots,N$, with local constraints $Co_i(x_i, u_i) \le 0$.

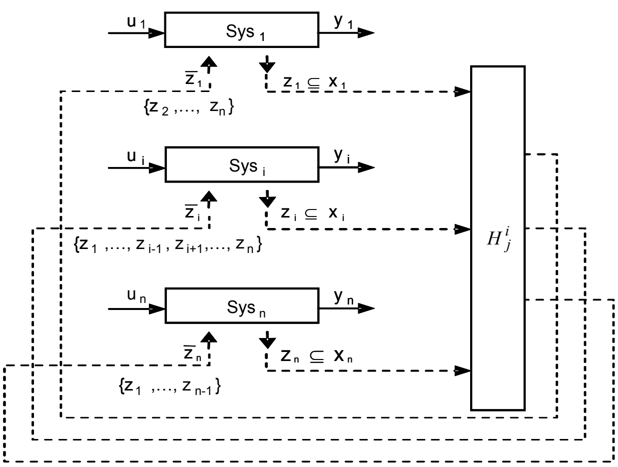

Fig. 1 Network of Inter-connected sub-systems

The global control satisfies an *additively separable* measure of performance along with global constraints: $Co(x,u) \le 0$.

2.2 FTC Architecture for NCS

Section 2.1 effectively outlines a de-centralised control approach to the NCS. However, this structure is insufficient for FTC implementation. An alternative architecture (Patton *et al*, 2007) illustrated in Fig. 2 is obtained as a result using the *Interaction Prediction Principle* via an Autonomous Control and Supervision system (ACSS) (Sadati & Moment, 2005).

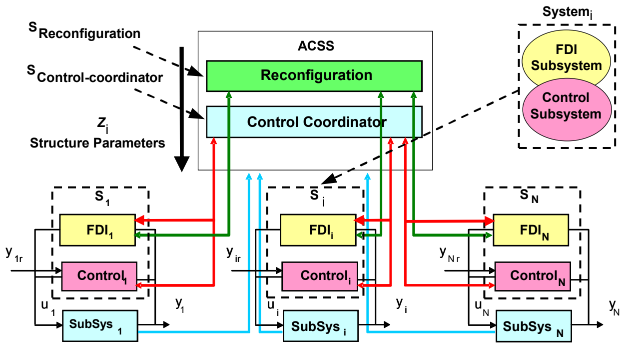

Fig. 2 A Fault-Tolerant Control Architecture for NCS

The motivation for this architecture is the concept of coordination of the activities of the various NCS subsystems. The coordinator has an ability to predict and coordinate possible interactions of these sub-systems. By using interaction predictions, the autonomous system coordinator, is able to use information regarding the current state of the system, and to predict and coordinate possible interactions between the sub-systems (Patton *et al*, 2007). This architecture encapsulates *four* main tasks:

1. A Control Coordination (Global Control) Task
2. *N* Local Control Tasks
3. *N* Local FDI Tasks
4. A Reconfiguration Task (for FTC of the NCS)

Control Coordination Task: The local systems require information which they do not have, but are available from a coordinator (Patton *et al*, 2007). An on-line recurrent neural network has been used to implement the Takahara *Interaction-Prediction Principle* (1965) in a reinforcement learning scheme (Haykin, 1994). The coordinator receives as inputs to its neural network the states $[x_1, x_2, \ldots, x_{n_i}]$ and local Lagrange multipliers $[\lambda_1, \lambda_2, \ldots \lambda_{n_i}]$ (see Patton et al, 2007). The coordinator then computes the new values of Lagrange multipliers $[\lambda_1^{new}, \lambda_2^{new}, \ldots \lambda_{n_i}^{new}]$ and interaction variables $[z_1^{new}, z_2^{new}, \ldots z_{n_i}^{new}]$, as inputs to the local optimal controllers. At each step the neural network weights are adjusted in the reinforcement learning algorithm and the interaction-prediction seeks to minimize the interactions between the subsystems through the coordinated local controllers. By updating the interaction variables z_i the coordinator effectively updates the $z_i = \sum_{j=1}^{N} H_j^i x_j$ in order to carry out the required balancing control to minimize the interactions. The interaction matrices are to be selected by an FDI unit to perform a robust decoupling of interactions.

Local Control Task: The required hierarchical structure of Fig. 2 is obtained by carrying out an analysis of the optimality conditions of the appropriate constrained optimal control problem (Patton, 2007). The analysis provides an *additively separable* Lagrangian (Singh & Titli, 1978) which has to be minimized in order to determine the local control inputs u_i , $i = 1,2,\ldots,N$.

The Lagrangian separates the various subsystem control signals, providing the required hierarchical decentralized architecture. Patton *et al (*2007) show that the subsystem control has *two* components based on: (a) local information and (b) the interactions between the subsystems.

FTC Properties of the Distributed Hierarchical NCS: There is always an interconnection component in each control signal which is at best only minimized by the interaction-prediction mechanism. Hence, the strategy and architecture of Fig.2 cannot be said to be tolerant to faults occurring at any place in the system, other than those occurring locally (Patton *et al* (2007). This is based on the coordination as well as interaction predictions the need for bounding the interaction effects is not required and assists in ensuring fault-tolerance (Patton *et al*, 2007). Sections 3&4 show how the interactions have an important effect on the robustness of the fault detection (and hence isolation).

Fault Description and FDI Tasks: The control coordination task states that a suitable FDI method must have a very specific role to play in enabling fault-tolerance in the NCS. The conditions under which the Control Coordinator (see Fig. 2) is unable to accommodate faults and hence change either the overall control requirements or to reconfigure the system must be determined. The FDI algorithms must distinguish between local and neighbouring subsystem faults. The nonlinear system description of (1) is extended to include the various faults acting in subsystems of the network as follows:

$$\left.\begin{aligned} \dot{x}_i &= F_i(x_i,z_i,u_i) = f_i(x_i,u_i) + \gamma_i f_{ai} + G_i(z_i) \\ y_i &= \rho_i(x_i) + D_i f_{ai} + \alpha_i f_{si} \end{aligned}\right\} \quad (3)$$

x_i, z_i, u_i have dimensions defined in (1). γ_i & D_i are distribution matrices for local actuator faults (f_{ai}) and α_i are distribution matrices for local sensor faults (f_{si}), all with appropriate dimensions, for $i = 1,.., N$. $G_i(z_i)$ represents an "unknown input" acting on the i^{th} subsystem, illustrating the variable nature of the interactions.

Subsystem Modelling: Although the approach requires an accurate model of the dynamics of the isolated subsystems and their interconnections, some very effective robustness concepts can be used. To identify suitable subsystems in this structure a recurrent neural network or genetic algorithm can be used (Kambhampati *et al,* 1997; Garces *et al,* 2003). The Local and Global Control Tasks are described in detail in Patton *et al* (2007). The robust FDI implementation based on this subsystem modelling is an important issue in this paper. The subsystem modelling relates to a linearised small signal representation of the i^{th} NCS subsystem (with faults), with the following structure.

$$\begin{aligned} \dot{x}_i &= A_i x_i + B_i u_i + \gamma_i f_{ai} + G_i(z_i) \\ y_i &= C_i x_i + D_i f_{ai} + \alpha_i f_{si} \end{aligned} \quad (4)$$

A particular interconnection structure is obtained as a result of the subsystem modelling. This structure is reflected in the elements of the matrix $G_i(z_i)$. From this, the z_i in (2) are selected by the coordinator to yield an estimate of the appropriate interconnections between a particular subsystem and its neighbours. It is assumed that the interconnection terms can be represented as:

$$G_i(z_i) = E_i z_i \quad (5)$$

The entries of E_i depend on which neighbouring subsystems interact with the i^{th} subsystem. The linearization is assumed not to change $G_i(z_i)$.

The interaction structure represented in (5) means that it is now possible to use the well known *unknown input* ($E_i z_i$) concept (Chen & Patton, 1999). For this application, the $i = 1, 2,\ldots, N$ unknown inputs are the interconnection variables z_i, whilst the E_i are computed due to the interaction imbalance in the distributed system. An extended UIO approach to robust FDI can now be used in which for each subsystem there is one UIO FDI estimator, taking account of interactions with nearest neighbours. *When decoupling of the unknown inputs is achieved, the faults in each subsystem can be detected and isolated using standard procedures.*

Reconfiguration Task: When large faults occur a form of reconfiguration of the system is necessary. If the estimated fault exceeds a pre-determined threshold the Reconfiguration Task will be triggered to (a) redistribute the performance requirements and (b) ensure that subsystems which have indicated a fault and are beyond repair do not cause a total system failure. It should be noted that although the presence of an FDI unit is essential, if the fault is bounded, reconfiguration is not required. The Control Coordinator will compensate for the fault, as it would assume that an error has occurred in the prediction of the interactions. The example given in Section 4 illustrates the function of this Task.

3. ROBUST FDI PRINCIPLES

For uncertain systems, disturbances, noise and modelling errors must all be taken into account. A Kalman filter is a special form of the traditional state observer for FDI that is designed in the sense of minimum estimation error variance, with the FDI residual signals depending on this estimation error to provide good fault detection and good fault isolation properties. There are two advantages of using a Kalman filter for FDI (Chen & Patton, 1996): (a) it provides a convenient gain update mechanism for on-line implementation and (b) it can be used to detect faults in the presence of both modelling errors and noise (due to the stochastic system description). The specific form of the Kalman filter used here is derived from the work of Chen and Patton (1996) as an approach to robust de-coupling of the effects of uncertain signal effects and disturbances, the so-called *unknown inputs* from the estimation error (and hence FDI residuals).

3.1 Unknown Input Observer Design for NCS Subsystems

This autonomous coordination and learning scheme is that it facilitates the interpretation of faults of a certain magnitude as "wrong interaction predictions". The coordinator accommodates these faults and ensures a smoother fault-tolerant operation of the system. However, this approach is naturally limited if the faults exceed certain magnitudes. Larger faults cannot be accommodated via the Takahara Principle and appropriate schemes for determining the fault magnitudes (or their effects) and locating them correctly is required. Hence, an appropriate FDI scheme has to be in place to facilitate the system fault-tolerance and recovery from large fault effect (Patton *et al*, 2007).

The following represents a continuous-time linear time-invariant state space formulation of each of the *N* subsystems, developed in (4). The *Unknown Input Observer* (UIO) is used in each subsystem as a special form of Kaman filter with decoupling of interconnection signals z_i (Fig. 3):

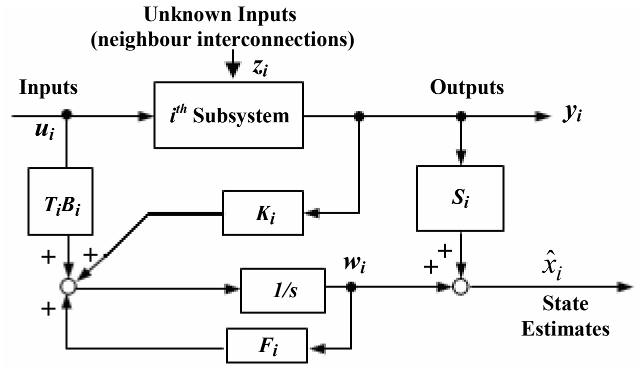

Fig. 3. Unknown Input Observer for i^{th} Subsystem

In Fig. 3 F_i, T_i, K_i and S_i are design matrices for the observer/estimator structure (Chen & Patton, 1999):

$$\begin{aligned} \dot{w}_i &= F_i w_i + T_i B_i u_i + K_i y_i \\ \hat{x}_i &= w_i + S_i y_i \end{aligned} \tag{6}$$

$\hat{x}_i$ is the estimate of the i^{th} subsystem state and y_i , u_i are the corresponding system output and input vectors.

Fig. 3 also shows the unknown inputs z_i (interconnection states) which must be removed by disturbance de-coupling, according to UIO theory. Here we use the well known Chen & Patton (1996) modified Kalman filter as a minimum variance state estimator in which the z_i are decoupled via the term $E_i z_i$ (see below). K_i is the *Kalman filter* gain matrix for the i^{th} subsystem filter, which depends upon the *Matrix Riccati* covariance update equations. The Kalman filter is of value as an estimator for this problem as the unknown input terms { $z_i = \sum_{j=1}^{N} H_j^i x_j$ } are updated at each cycle of the interaction-prediction process via the coordinator. The Kalman filter (in its modified form) provides a good mechanism for recursive on-line decoupling of these terms. This is especially true if the discrete-time formulation of the Kalman filter is used. Here we outline the Kalman filter structure in continuous-time for convenience of notation and compactness. Chen & Patton (1996, 1999) describe the following conditions to achieve disturbance de-coupling for the optimal observer described above:

$$(S_i C_i - I_i) E_i = 0 \tag{7}$$

$$T_i = I_i - S_i C_i \tag{8}$$

$$F_i = A_i - S_i C_i A_i - K_{i_1} C_i \tag{9}$$

$$K_{i_2} = F_i S_i \tag{10}$$

The modified Kalman gain is computed recursively as:

$$K_i = K_{i_1} + K_{i_2} \tag{11}$$

Note that, for the case of no-decoupling of interaction faults, $S_i = 0$, and $K_i = K_{i_1}$, and $\hat{x}_i = w_i$,which corresponds to the standard Kalman filter formulation.

3.2 Robust Residual Generation

To implement a robust FDI scheme a residual signal r_i must be derived from the subsystem state estimates $\hat{x}_i$ which is also robust against the unknown inputs (inter-connection states) z_i. The residual is generated as (Chen & Patton, 1999):

$$r_i = y_i - \hat{y}_i = (I_i - C_i S_i) y_i - C_i w_i \tag{12}$$

When the estimator (6) is applied to (4), the z_i are assumed to be decoupled from the model system and the resulting estimation error $[e_i = x_i - \hat{x}_i]$ is governed by the following:

$$\dot{e}_i = F_i e_i - K_{i_1} \gamma_i f_{si} - S_i \alpha_i \dot{f}_{si} + T_i \gamma_i f_{ai} \tag{13}$$

$$r_i = C_i e_i + D_i f_{ai} + \alpha_i f_{si} \tag{14}$$

Hence, $\varepsilon\{e_i\} \to 0$ and $\varepsilon\{\hat{x}_i\} \to \varepsilon\{x_i\}$ if the matrix F_i is stable, where $\varepsilon\{\cdot\}$ denotes the expectation operator. For the UIO de-coupling Kalman filter the necessary and sufficient condition for the existence of a solution to (7) has been given by Chen & Patton (1996) as:

$$rank(C_i E_i) = rank(E_i) \tag{15}$$

A special solution is given by:

$$S_i^* = E_i[(C_i E_i)^T C_i E_i]^{-1} (C_i E_i)^T \tag{16}$$

S_i^* is the left-inverse of S_i and the matrix K_{i_1} is designed to stabilise the observer/filter and achieve minimum state estimation error variance of the fault-free system. The unknown disturbance term $E_i z_i$ does not affect the residual, *i.e.* the residual is robust against the interconnection signals. As the state estimation error e_i has minimum variance, the fault-free residual is also optimal with respect to noise (with assumed statistics), i.e. the residual is not affected by the unknown input (interconnections) z_i and is optimal with respect to noise due to the minimal variance property of the state estimation error e_i (Chen & Patton, 1999).

4. DISTRIBUTED SYSTEM APPLICATION EXAMPLE

To illustrate the discussion above a tutorial example of a 3-tank inter-connected system is used here as a benchmark problem of the "Networked Control Systems: Tolerant to faults (NeCST)" FP6 STREP project http://www.strep-necst.org/ (Sauter *et al*, 2005).

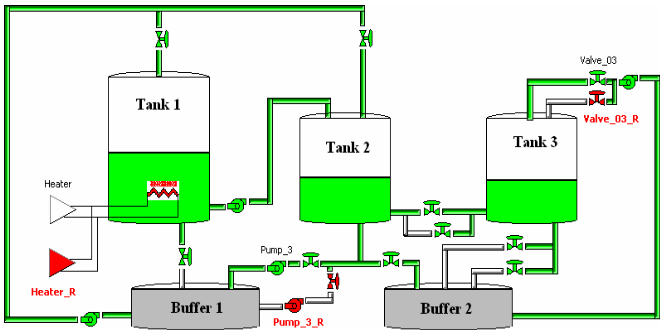

Fig. 4. Three-Tank system with redundant elements

The system is simulated within the Matlab/LabVIEW environment using the following performance objectives::

1. Maintain the tank levels, L_1 at 0.75 m, L_2 at 0.3 m and L_3 at 0.5 m.

2. Maintain the temperature of Tanks 1 & 2, T_1 at 30^{o}C & T_2 at 28^{o}C.

The system is simulated initially without any faults and the outputs track the reference signals (see Patton *et al,* 2007).

When a fault exceeds a certain level the FTC under autonomous coordination (without reconfiguration) no longer tolerates the faults, so that the NCS requires reconfiguration. The Reconfiguration Task acquires residual information from the FDI Tanks and makes a decision as to whether or not the reconfiguration is required, based on the residual signals (see Fig. 2). The reconfiguration is accomplished by the redundant actuators included to the system. There are one heater (Heater_R), one pump *(Pump_3_R) and one valve (Valve_03_R) as redundant elements* (See Fig. 4). In order to illustrate the reconfiguration three experiments was carried out. As stated above there are 3 hardware redundancies in the system: Heater_R, Pump_3_R and Valve_03_R. Thus when severe faults occur on Heater, Pump_3 or Valve_03 that FTC strategies cannot compensate the faults the mentioned redundant elements of the system will take place.

When the fault magnitude is too large the control scheme cannot compensate for the faults. When a fault is introduced into the Heater in Tank-1, T_1 moves away from its set-point value, the residual signal reaches the chosen threshold level and the Reconfiguration Task disconnects the Heater and activates the redundant Heater_R.

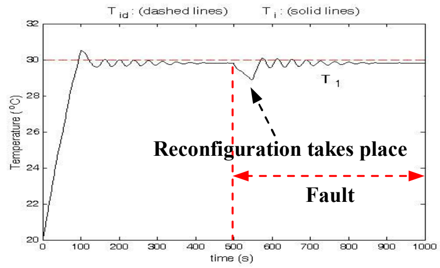

Fig. 5. The temperature of Tanks-1 *with heater fault and the reconfiguration takes place at t = 550*

Fig. 5 shows that after reconfiguration T1 soon settles back to its normal value under coordinated closed-loop control. The hierarchical scheme and robust FTC/FDI methodology are able to distinguish between local faults and faults external to the local system.

The purpose of Figs. 6 to 11 is to illustrate the robustness of residuals to interconnection faults, based on the levels L1, L2 & L3 and Temperatures T1 & T2 and inter-tank flows V12, V20 and V32. The fault condition is as for Fig. 5. Figs. 6 to 8 correspond to the case when the 3 UIO modified Kalman filters are implemented, demonstrating clearly that the T1 residual can be used to isolate the heater fault.

In the case of Figs. 9 to 11 the standard Kalman filter (with the same Q, R and P0 matrices as for case of Figs. 6 to 8) is used for each subsystem, showing clearly the inability to isolate the heater fault via the T1 measurement in Tank-1.

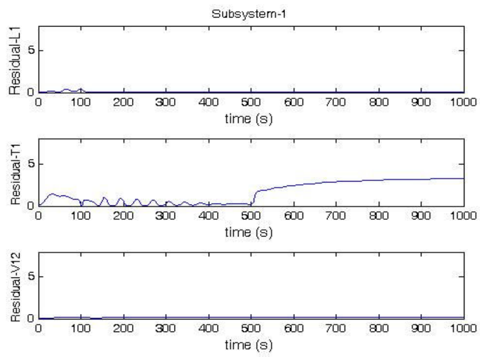

Fig. 6 Residual signals with decoupling (Tank-1)

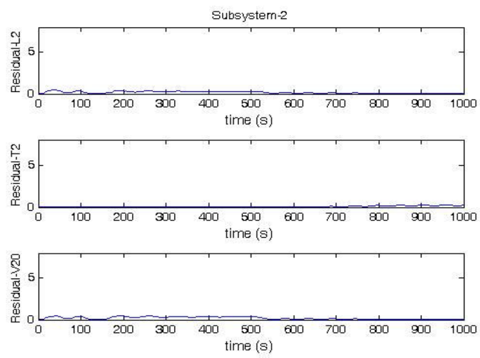

Fig. 7 Residual signals with decoupling (Tank-2)

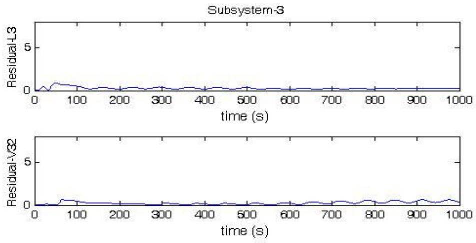

Fig. 8 Residual signals with decoupling (Tank-3)

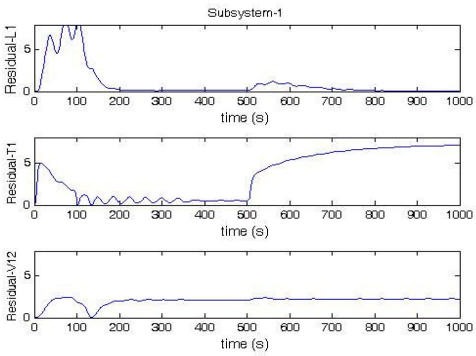

Fig. 9 Residual signals - no decoupling (Tank-1)

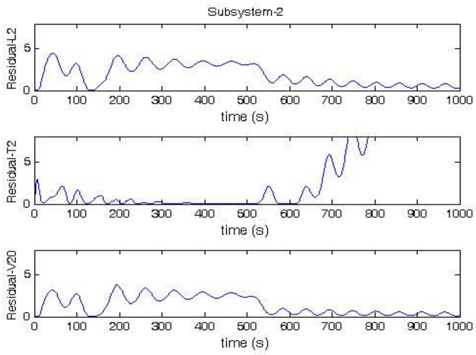

Fig. 10 Residual signals - no decoupling (Tank-2)

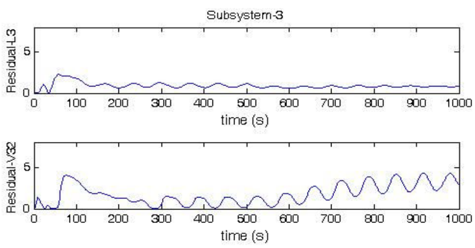

Fig. 11 Residual signals - no decoupling (Tank-3)

5. CONCLUSIONS

The concept of an autonomously coordinated distributed control system has been extended to include active reconfiguration via robust FDI, thereby developing a paradigm for FTC in NCS. In this form the paradigm is limited to an infinite bandwidth Control Network Description of the NCS as this is necessary to establish a suitable FTC architecture and tools for autonomy. The work describes a new development of the well-known UIO robust FDI filter, extended to deal with the robust de-coupling of subsystem faults, yielding a mechanism for reliable fault isolation and system reconfiguration. The concepts have been illustrated using a non-linear simulation of a complex 3-Tank system with built-in redundancy. Due to space limitations descriptions of the fault detectability/isolability properties of the UIO filters has been omitted, as well as the details of the reconfiguration mechanism.

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