Robust Fault Isolation for Autonomous Coordination in NCS

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Abstract: A recent study shows that a given hierarchical decentralized control system architecture may be suitable for autonomous coordination of fault-tolerant control (FTC) in a network of distributed and inter-connected subsystems. This paper focuses on the development of a robust Fault Detection and Isolation (FDI) strategy for this Network Control System (NCS) FTC problem. By using a robust form of the Unknown Input Observer (UIO), the subsystems can be effectively decoupled from each other for diagnostic purposes. The effects of subsystem interactions are removed from the FDI residuals, thus facilitating a powerful way to achieve robust local subsystem FDI. This subsystem isolation forms a part of the decision-making process of the autonomous system coordinator, facilitating a strategy for autonomy in FTC for NCS.

1. INTRODUCTION

The NCS concept began to attract the attention of academic researchers in the 1990s due to amazing advantages of flexibility, reconfigurability, etc. A considerable volume of theoretical tools have emerged which now extend to encompass FTC approaches to NCS, including the use of two-level hierarchical and distributed control (Patton *et al*, 2007). 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 complex distributed system structure in terms of inter-connections, over-lapping decompositions and redundancy (Singh *et al*, 1983; Chen & Stankovic, 2005). The NCS problem can be partitioned into a distributed control design, based on a "physical" network and a communications network involving communication delays and bandwidth limitations etc. The large-scale systems theory of the 1970s was based only on the physical network, whereas in the complete NCS problem the communications network gives rise to additional complexity in terms of network constraints (delays and bandwidth limitations, etc).

This paper uses the distributed control systems concept considering only the physical network (i.e. assuming a network of infinite bandwidth), based on a suitable architecture for achieving reliable FTC in NCS, under autonomous system operation (Patton *et al*, 2007). This approach requires reliable local FDI, at subsystem level. Faults within subsystems must be detected and isolated reliably in the presence of subsystem interactions.

Robustness in FDI (see for example, 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 a robust FDI strategy must be based on the principle of diagnosis within a given subsystem. The interactions between subsystems can be considered as "unknown inputs". The coupling effects can be de-coupled or minimized using a variety of recently developed robust FDI methods, based on H_∞, Linear Parameter-Varying (LPV) systems (Bokor & Balas, 2004; Casavola *et al*, 2007) or the *unknown input observer* (applied in the context of robust FDI design) (Chen & Patton, 1996, 1999; Pertew *et al*, 2005).

The determination of the network subsystems and an in-depth description of the NCS architecture and strategy for autonomous control in an FTC context has been described earlier (Patton *et al*, 2007). This paper shows how the required robust decoupling can be achieved directly via a UIO FDI filter/estimator applied to each NCS subsystem. The estimated subsystem interactions (unknown inputs) are decoupled directly by design, thus enhancing the robust detectability and isolability of the distributed system faults. Robust UIO FDI residuals provide fault information to an autonomous learning system coordinator to facilitate FTC NCS reconfiguration. This concept has been described in Patton *et al* (2007) and this paper focuses on (a) the subsystem interaction de-coupling problem and (b) robust FDI in terms of robust isolation of individual faults within each subsystem.

Section 2 outlines the autonomous fault-tolerant NCS architecture of a suitably chosen hierarchical network of distributed subsystems. Section 3 outlines the principles of robust FDI based on well-known UIO FDI theory (Chen *et al,* 1996; Chen *et al,* 1999) as applied to the problem of robust de-coupling of subsystem interconnection faults. Section 4 outlines a benchmark study example of a distributed 3-Tank system. Results demonstrate the robust FDI design performance (for different fault levels) within the autonomous NCS scheme, providing a good mechanism for autonomous FTC. Section 5 gives concluding remarks.

2. NCS PROBLEM STATEMENT

Control over a network can be formulated through the concept of 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) for which network communication faults (time-delays etc) are of no consequence to the control performance. This implies that single-rate sampling is sufficient and the problem description can be given in continuous time. Clearly, this is one possible view of the NCS as a network structure. An alternative view, based on a network of communication links can be incorporated at a later stage, together with appropriate network faults (time-delays, multi-rate sampling, etc). As a matter of fact almost all papers on control over NCS networks only consider this second network, thereby limiting the scope for developing the autonomous control that is thought to be necessary in a network FTC application.

2.1 N Interconnected Subsystems

Whilst a number of distributed control strategies can be used, a distributed hierarchical and interconnected structure means that a multi-level-multi-objective approach can be used, based on constrained optimal control (Singh & Titli, 1978; Patton *et al*, 2007). This problem is naturally posed in state space and the *receding horizon* control problem fits well to this formulation (Goodwin *et al*, 2004). Each subsystem of this distributed system (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: $(x_i, z_i, u_i) \rightarrow F_i(x_i, z_i, u_i) : \Re^{n_i} \times \Re^{l_i} \times \Re^{r_i} \rightarrow \Re^{n_i}$, x_i , z_i and u_i are the states, inter-connections and inputs of the i^{th} subsystem component, *i = 1,2,…,N*. Furthermore, $(x_i, u_i) \rightarrow f_i(x_i, u_i) : \Re^{n_i} \times \Re^{r_i} \rightarrow \Re^{n_i}$ is a local (or isolated system) model of the i^{th} subsystem, and $(z_i) \rightarrow G_i(z_i) : \Re^{l_i} \rightarrow \Re^{l_i}$ are non-linear inter-connection mappings involving the subsystem connections. The *i = 1,2,…, N* interconnection states are (Patton *et al* (2007):

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

The H_j^i are $\Re^i \times \Re^j$ matrices describing the interconnections between the subsystems. The subsystem control performances (see Patton *et al*, 2007) are measured, based on linearised subsystem models, via local cost functions: $J_i(x_i, t; u_i)$, *i = 1,2…,N,* with local constraints $Co_i(x_i, u_i) \leq 0$. The global control satisfies an *additively separable* measure of performance along with global constraints: $Co(x,u) \leq 0$ (Patton *et al*, 2007)

2.2 FTC Architecture for NCS

Section 2.1 effectively outlines a de-centralised control approach to the NCS problem. This structure is insufficient for FTC implementations. An alternative architecture (Patton *et al*, 2007) is illustrated in Fig. 2, using an autonomous learning coordinator based on the *Interaction Prediction Principle* (Takahara, 1965; Sadati & Momeni, 2005).

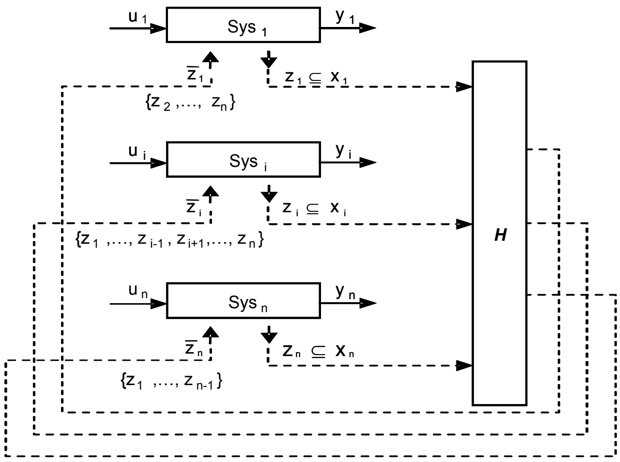

Fig. 1 Network of Inter-connected sub-systems

This architecture incorporates the concept of coordination of the activities of various NCS subsystems. The coordinator predicts and coordinates possible subsystem interactions.

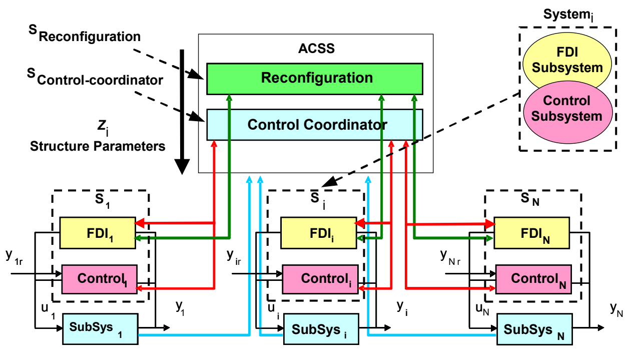

Fig. 2 A Fault-Tolerant Control Architecture for NCS

Through interaction predictions, the autonomous system coordinator, is able to use information regarding the current system state, and to predict and coordinate possible interactions between 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* (Sadati & Momeni, 2005) 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 interaction variables z_i 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 two-level hierarchical structure of Fig. 2 is obtained by carrying out an analysis of the optimality conditions of the appropriate constrained optimal control problem (Patton *et al*, 2007). This yields 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 control Lagrangian separates the various subsystem control signals within the required hierarchical decentralized architecture. Patton *et al (*2007) show that the subsystem control has *two* components based on: (a) local information and (b) subsystem interactions.

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). As this is based on the coordination as well as interaction predictions the need for bounding the interaction effects is not required and this 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). $y_i \in \Re^{m_i}$, 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 $i = 1,\ldots, N$. $G_i(z_i)$ 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 system reconfiguration 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. The role of the coordination task has been described in (Patton *et al*, 2007).

3. ROBUST FDI PRINCIPLES

For uncertain systems, disturbances, noise and modelling errors must all be taken into account. A Kalman filter is used in the sense of minimum estimation error variance, with the FDI residual signals depending on the estimation error to provide good FDI 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 is attributed to Chen & 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 effects (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 Observer or Kaman filter with decoupling of interconnection signals z_i (Fig. 3):

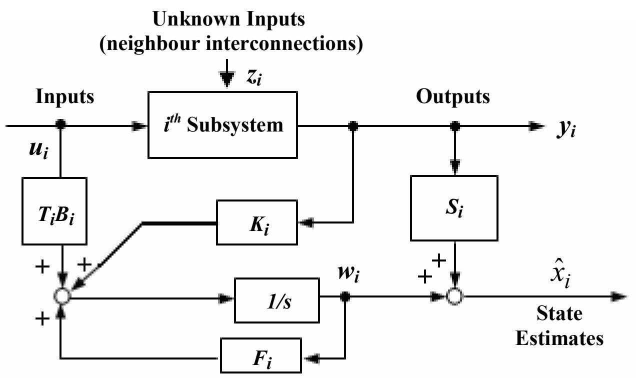

Fig. 3. Unknown Input Observer for i^{th} Subsystem

In Fig. 3 F_i, T_i, K_i and S_i are design matrices for the UIO/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 the well known Chen & Patton (1996) modified Kalman filter is used, as a minimum variance state estimator in which the z_i are decoupled via the term $E_i z_i$ (see below). Recall that this work is concerned with the distributed fault-tolerant system coordination problem. For this purpose the Kalman filter estimator is used here in the UIO_i filter role as the unknown input terms z_i are updated at each cycle of the interaction-prediction process via the coordinator. The Chen & Patton Kalman filter (1996) provides a good mechanism for recursive on-line decoupling of the unknown inputs. K_i is the Kalman gain matrix for the discrete-time i^{th} subsystem UIO_i filter. In general, this recursive formulation is particularly useful for implementing unknown input de-coupling updates, as they occur.

For convenience of notation, compactness, and to better illustrate the concepts, the following UIO_i structure is described in continuous-time format. The original work is described in discrete-time (Chen & Patton, 1996). However both formulations are given in Chen and Patton (1999). The following conditions are used to achieve disturbance de-coupling for the optimal observer described above:

$$(S_iC_i - I_i)E_i = 0 \tag{7}$$
$$T_i = I_i - S_iC_i \tag{8}$$
$$F_i = A_i - S_iC_iA_i - K_{i_1}C_i \tag{9}$$
$$K_{i_2} = F_iS_i \tag{10}$$

The Chen & Patton Kalman gain is computed recursively as:

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

K_{i_2} takes account of the effects of the unknown input terms $E_i z_i$. For the case of no-decoupling of interaction faults, $S_i = 0$, and $K_i = K_{i_1}$, and $\hat{x}_i = w_i$, corresponding 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):

$$r_i = y_i - \hat{y}_i = (I_i - C_iS_i)y_i - C_iw \tag{12}$$

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

$$\dot{e}_i = F_ie_i - K_{i_1}\gamma_i f_{si} - S_i\alpha_i\dot{f}_{si} + T_i\gamma_i f_{ai} \tag{13}$$
$$r_i = C_ie_i + D_if_{ai} + \alpha_i f_{si} \tag{14}$$

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 UIO de-coupling the necessary and sufficient condition for the existence of a solution to (7) (Chen & Patton, 1996) as:

$$Rank(C_iE_i) = rank(E_i) \tag{15}$$

A solution that satisfies this condition is given by:

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

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_iz_i does not affect the residual, *i.e.* the i^{th} 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).

3.3. Structure residual set generation for fault detection and isolation

When sensor and actuator faults are considered, Fig 4 describes the robust FDI scheme comprising a group of four FDI filters: *(i)* one is based on the nominal fault-free system behaviour (*used for fault detection*), *(ii)* three (*used for fault isolation*) are each based on the three separate faults considered in this study (heater: T1, pump: P3 and Clogging on pipe inlet in Tank-3). This bank of filters and residual generators facilitates the isolation of these 3 faults via a structured residual design procedure. Each filter in the bank is driven by the same set of all the system inputs and outputs. Taking the difference between the system and filter outputs, the generated residual signals are used to detect and isolate faults. Each filter each residual has a specific sensitivity to a particular fault, whilst insensitive to the remaining two faults. The UIO_i *-0* is design only for fault detection. It decouples only the interconnection disturbance terms and the fault directions are not considered. This residual can be used to detect faults according to simple threshold logic:

$$\begin{aligned} \left\| r_i^0 \right\| &< Threshold \qquad for\ fault-free\ case \\ \left\| r_i^0 \right\| &\geq Threshold \qquad for\ faulty\ cases \end{aligned}$$

To achieve fault isolation, *a structure residual set* can be used (Gertler, 1991) in the following way. UIO_i *-1*, *2* and *3* each generate residuals which are sensitive to only one fault (using the *decoupling of unknown input concept*), thus makes the isolation achievable. The system from Fig 4 can be described by the following continuous-time equations:

$$\begin{aligned} \dot{x}_i &= A_ix_i + B_i^{\pi}u_i^{\pi} + B_i^{\pi}f_{ai}^{\pi} + b_{\pi i}[u_{\pi i} + f_{a\pi i}] + E_iz_i \\ y_i^{\lambda} &= C_i^{\lambda}x_i + f_{si}^{\lambda} \\ y_{\lambda i} &= c_{\lambda i}x_i + f_{s\lambda i} \end{aligned} \quad (17)$$

for: $\lambda = 1,2,\ldots,m_i$ and $\pi = 1,2,\ldots,r_i$

where $c_{\lambda i} \in \Re^{1xn_i}$ is the λ^{th} row of the matrix C_i, $C_i^{\lambda} \in \Re^{(m_i-1)xn_i}$ is obtained from matrix C_i by deleting λ^{th} row $c_{\lambda i}$, $y_{\lambda i}$ is the λ^{th} component of y_i and $y_i^{\lambda} \in \Re^{m_i-1}$ is obtained from vector y_i by deleting λ^{th} component $y_{\lambda i}$.

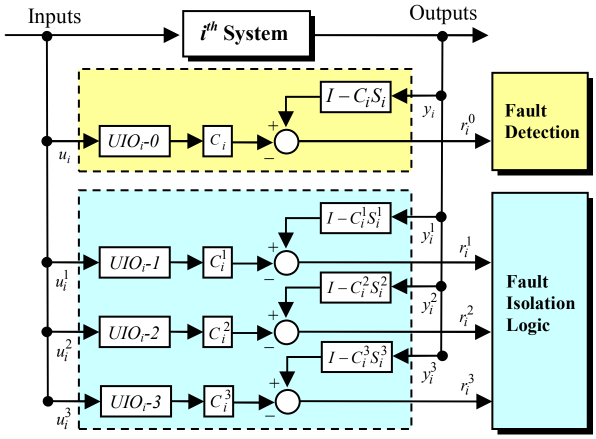

Fig. 4. Robust Fault Detection and Isolation Scheme

And $b_{\pi i} \in \Re^{n_i}$ is the π^{th} column of B_i, $B_i^{\pi} \in \Re^{n_ix(r_i-1)}$ is obtained from the B_i by deleting the π^{th} column $b_{\pi i}$, $u_{\pi i}$ is the π^{th} component of u_i, $u_i^{\pi} \in \Re^{r_i-1}$ is obtained from the vector u_i by deleting π^{th} component of $u_{\pi i}$.

Note that the unknown input concept can be generalised to include the fault signals as if they are themselves unknown inputs. In this way, and if the existence conditions in (7)-(16) hold true (see Sections 3.1 & 3.2), (17) can be applied to the robust residual fault isolation problem, considering either actuator or sensor faults (or both) (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) (See Fig. 5).

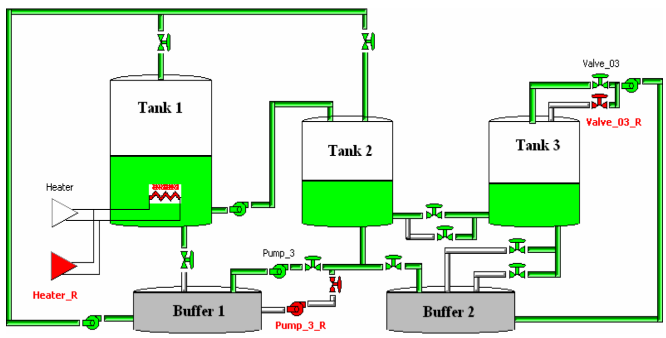

Fig. 5. *3*-Tank inter-connected system

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°C & T_2 at 28°C.

When a fault is introduced into the Heater in Tank-1 at t = *500*, 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 & 7 is to illustrate the robustness of residuals to interconnection faults (Detection & Isolation), based on the levels L_1, L_2 & L_3 and Temperatures T_1 & T_2 and inter-tank flows V_{12}, V_{20} and V_{32} (Patton *et al*, 2007).

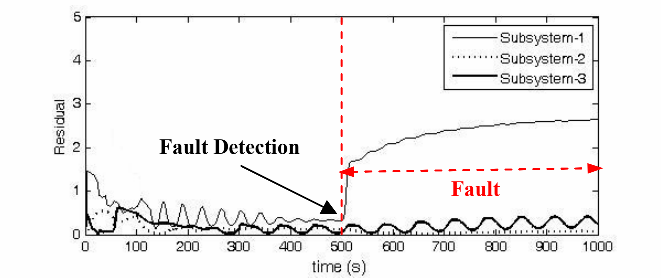

Fig. 6. *3*-Residual signals for "Fault Detection" using *Fault Detection Observer* (*UIO_i-0*)

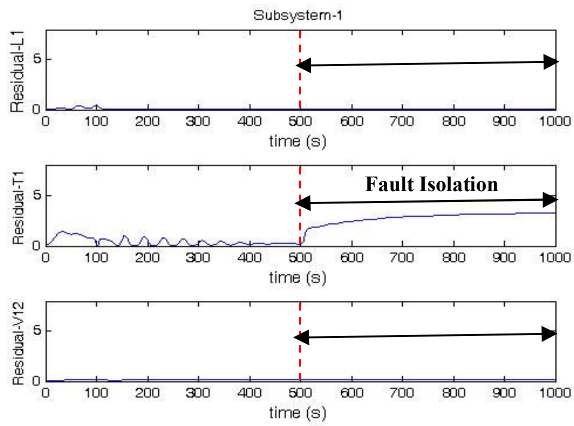

Fig. 7. Residual signals for "Fault Isolation" using the bank of *Fault Isolation Observers* (*UIO_i -1*, *2* & *3*)

Figs. 6 & 7 correspond to the case when the UIO-modified Kalman filters are implemented, demonstrating clearly that the T_1 residual can be used to detect and isolate the heater fault.

5. CONCLUSIONS

The concept of an autonomously coordinated distributed control system is 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 special application of the well-known UIO robust FDI filter, extended to deal with the robust de-coupling of subsystem faults and further extended to consider robust fault isolation within each subsystem. The robust FDI approach provides a mechanism for reliable fault isolation and system reconfiguration in NCS. The concepts are illustrated using a non-linear simulation of a complex 3-Tank system with built-in redundancy.

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