

Reconfiguration control strategy using Takagi–Sugeno model predictive control for network control systems – a magnetic levitation case study

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Abstract: This paper presents a reconfiguration control strategy for network control systems that makes use of a fuzzy Takagi–Sugeno model for predictive control. The dynamic behaviour of a network control system is modelled by using a real-time implementation of the scheduling algorithm. Here, this is applied for a magnetic levitation system, as a plant that is also modelled using a fuzzy Takagi–Sugeno approach. Thus this paper covers several design issues, such as how to model a computer network, a plant, and a reconfiguration control strategy, as well as how the reconfiguration control strategy is modified using the fuzzy approach.

Keywords: reconfiguration control strategy, network control systems, fuzzy Takagi–Sugeno, model predictive control, real-time, magnetic levitation system, fault isolation, time delay modification

1 INTRODUCTION

Reconfiguration is a transition that modifies the structure of a system so it changes its representation of states. Here, it is used as a feasible approach for fault isolation, and it is also a response to time delay modification. In control systems, several modelling strategies for managing time delay within control laws have been studied by different research groups. Nilsson [1] proposes the use of a time delay scheme integrated to a reconfigurable control strategy, based on a stochastic methodology; Jiang and Zhao [2] describe how time delays are used as uncertainties, which modify pole placement of a robust control law; Izadi and Blanke [3] present an interesting case of a fault-tolerant control approach related to time delay coupling; Lian *et al.* [4] present a modelling of the dynamic system considering time delays due to communication networks (which is the basis for the present approach); Blanke *et al.* [5] study reconfigurable control from the point of view of structural modification, establishing a

logical relation between dynamic variables and the respective faults; Thompson [6] and Benítez-Pérez and Garcia-Nocetti [7] consider that reconfigurable control strategies perform a combined modification of system structure and dynamic response, and thus this approach has the advantage of bounded modifications over system response; and finally, Almeida *et al.* [8] present a scheduling management for real-time distributed systems which aids the understanding of the time delay due to factors external to the distributed system, such as faults.

Normally, when a fault occurs during the operation of a system, a respective fault tolerance strategy is applied. However, applying such a fault tolerance strategy is not enough to maintain the performance of the system, since dynamic conditions are modified. Therefore, it seems to be necessary to take into account current conditions in order to maintain system performance, even degraded performance. Thus, this paper proposes a novel technique based on fuzzy model predictive control (MPC), and considering bounded variable time delays. Here, local faults and inherent time delays are used as necessary conditions for control design.

The approach adopted here makes use of a case study that takes time delays due to communication

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5. An important constraint is that ART-2A cannot learn new plans during the on-line stage, as a safety precaution.

For a NCS, the communication network strongly affects the dynamics of the system, expressed as a time variance that exposes a non-linear behaviour. Such non-linearity is addressed by incorporating time delays. From real-time system theory, it is known that time delays are bounded even in the case of causal modifications due to external effects. Using this representation, time delays are counted using simple addition, as described in the Section 3.

3 CASE STUDY AND RECONFIGURATION APPROACH

The case study here is a magnetic system integrated to a computer network as shown in Fig. 2 [15]. The dynamics of this case study are expressed in terms of a transfer function as

$$G_{bi}(s) = \frac{-k_{bdc}w_b^2}{s^2 - w_b^2}$$

$$k_{bdc} = \frac{x_{bo}}{I_{co}}$$

$$w_b = \sqrt{\frac{2g}{x_{bo}}}$$

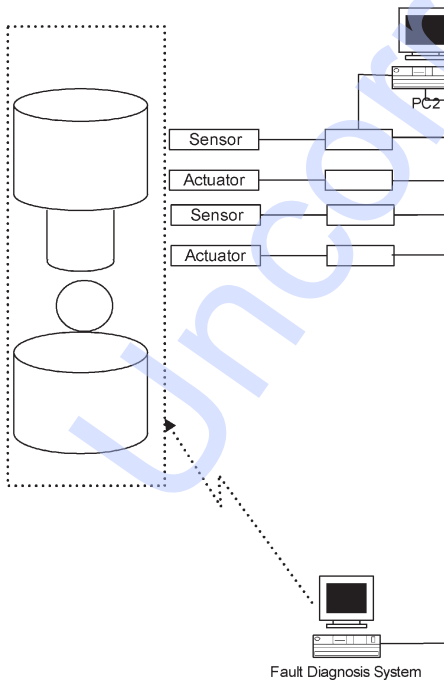


Fig. 2 Magnetic levitator case study

where

g is the force of gravity;

I_{co} is the current in the coil;

x_{bo} is the distance from coil to the ball position.

For experimental purposes, Fig. 3 presents a time diagram for a fault-free scenario, while Fig. 4 presents a time diagram for a fault scenario considering fault masking. In both these figures, s_1 and s_2 represent optic sensor nodes (in this case two light sensors are used), C is the control node, and A_1 is the actuator node. When a fault occurs, EDF is used, and the ART-2A re-organizes task execution according to time restrictions. Notice that in Fig. 3 and Fig. 4 the maximum time delays are bounded.

Both scenarios are local with respect to the magnetic levitation system: they are not periodic, although nodes are periodic. As both scenarios are bounded, the consumption times are expressed as equation (3) and equation (4) (from Fig. 3 and Fig. 4, respectively). For a fault-free scenario, time delay is

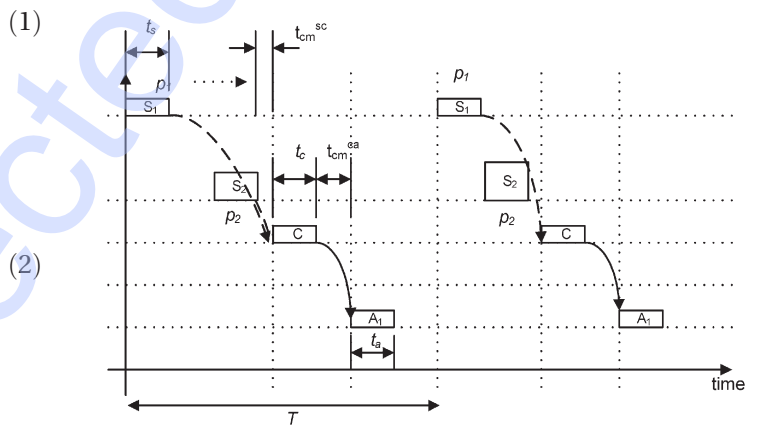


Fig. 3 Fault-free scenario

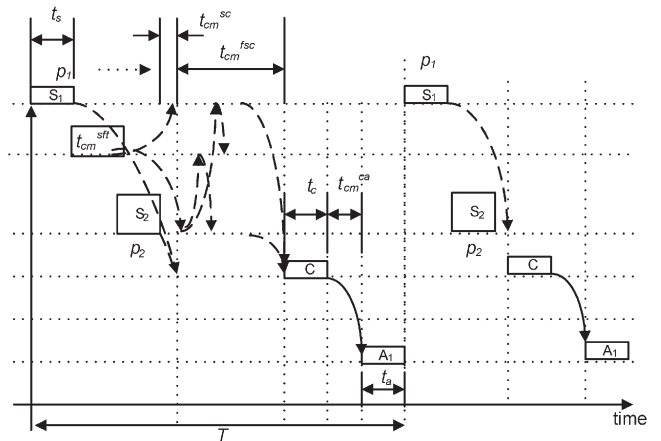


Fig. 4 Fault scenario considering fault masking

expressed as

$$T = 3t_s + t_{cm}^{sc} + t_c + t_{cm}^{ca} + t_a \quad (3)$$

while for a fault scenario, time delay is expressed as

$$T = 3t_s + t_{cm}^{sc} + t_{cm}^{sft} + t_{cm}^{fsc} + t_c + t_{cm}^{ca} + t_a \quad (4)$$

where

- t_s is the time consumed by sensors;
- t_{cm}^{sc} is the communication time between sensor and control;
- t_{cm}^{sft} is the communication time between sensor and fault tolerance module;
- p_1 and p_2 are consumption delays;
- t_{cm}^{fsc} is the time consumed for the fault sensor to send messages to its neighbour and produce agreement;
- t_c is the time consumed by the control node;
- t_{cm}^{ca} is the communication time between controller and actuator;
- t_a is the time consumed by the actuator.

Time values of these delays are averaging among components. From both scenarios, a *fault tolerance* element is defined as one that represents some extra communication for control performance, although it masks any local fault from sensors. From this time boundary, in both scenarios, it is feasible to implement some control strategies. Considering this, two possible fault cases are feasible:

- (a) one local fault;
- (b) several local faults.

From these two possible fault cases, the latter is a worst-case scenario, related to several local faults that have an impact on the global control strategy. However, the first case presents a minor degradation on the global control strategy. Despite this degradation, the system is expected to keep its functionality given the fault tolerance strategy and the local time

delays integrated into related controllers. Faults are local failures of light capture on each optic sensor (three sensors are used). The fault-tolerant strategy is performed within the fault-tolerance element. Local faults are related to local values' deviations from current measures. Moreover, such local faults are neither catastrophic, nor permanent.

Considering the two possible fault cases, Table 1 contains the measured values for local and global time delays. As the time delays are bounded, the plant model is defined as an integration of the original plant and the control, i.e. from an integration of equation (1) and equation (2) (Fig. 5).

The plant model has the following dynamics

$$\begin{aligned} x(k+1) &= a^p x(k) + B^p u(k) \\ y &= c^p x(k) \end{aligned} \quad (5)$$

where:

- $a^p \in \mathbb{R}^{n \times n}$;
- $c^p \in \mathbb{R}^{1 \times n}$;
- $B^p \in \mathbb{R}^{n \times 1}$ are matrices related to the plant;
- $x(k)$, $u(k)$, and $y(k)$ are states, inputs, and outputs, respectively.

In particular, B^p is defined as:

$$B^p = \sum_{i=1}^N \rho_i B_i \sum_{j=1}^M \int e^{-a^p(t-\tau)} d\tau \quad (6)$$

where

$$\rho_i = \{0, 1\}, \quad \sum_{i=1}^N \rho_i = 1;$$

Table 1 Time delays related to local communications

Configuration 1	Local time delays	1 ms
Several local faults	Global time delays	5 ms
Configuration 2	Local time delays	1 ms
One local faults	Global time delays	3 ms

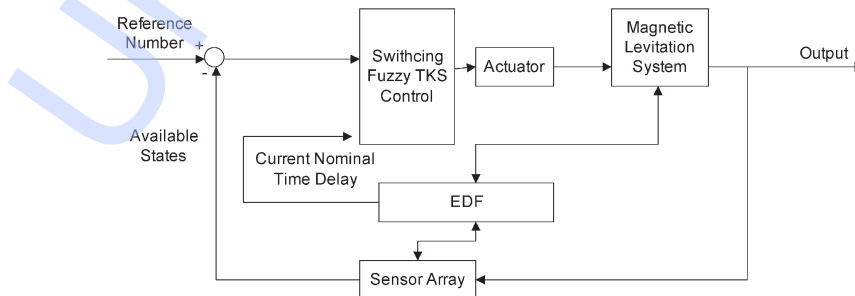


Fig. 5 Plant and control integration

N is the total number of possible faults;
 M is the involved time delays from each fault;
 τ_{j-1}^i and τ_j^i are current communication time delay,
 $\sum_{j=1}^M \tau_j^i \leq T$ where T is the total transport delay of the cycle and depends on the faults scenarios.

Thus, B_i is an array

$$B_i = \begin{bmatrix} b_1 \\ b_2 \\ 0_i \\ \vdots \end{bmatrix}$$

where

$b_1 \rightarrow b_N$ are the elements conformed at the input of the plant (such as actuators);
 0_i is the lost element due to local actuator fault.

B^p represents only one scenario (equation (6)). A further definition of a current B_i^p considers local actuator faults and related time delays:

$$B_i^p = B_i \sum_{j=1}^M \int_{\tau_j^i}^{\tau_{j-1}^i} e^{-a^p(t-\tau)} d\tau \quad (7)$$

For simplicity, B_i^p is used in order to describe local linear plants.

From this representation, a fuzzy plant is defined as follows, taking into consideration each time delay, fault cases, and the related fuzzy rules

$$r_i : \text{if } x_1 \text{ is } \mu_{1i} \text{ and } x_2 \text{ is } \mu_{2i} \text{ and } \dots \text{ and } x_l \text{ is } \mu_{li} \\ \text{then } a_i^p x(k) + B_i^p u(k) \quad (8)$$

where

$\{x_1 x_2 \dots x_l\}$ are current state measures;
 l is the number of states;
 $i = \{1, \dots, N\}$ is one of the fuzzy rules;
 N is the number of the rules, which is equal to the number of possible faults;
 μ_{ij} are the related membership functions, which are Gaussian defined as

$$\mu_{ij}(y_x, u_x) = \exp \left[- \left(\frac{y_x - c_{ij}^y}{\sigma_{ij}^y} \right)^2 - \left(\frac{u_x - c_{ij}^u}{\sigma_{ij}^u} \right)^2 \right] \quad (9)$$

where c_{ij} and σ_{ij} are parameters to be tuned.

The representation of the plant as an integrated system with the control is thus based on the centre of area de-fuzzification method [16]. From this representation of a global non-linear system, it is necessary to define a global stability condition as a result of this fuzzy system. This is given considering the fuzzy logic control approach. The result allows the integration of the non-linear stages and transitions basically to a group of linear plants. From the point of view of the approach, taking the input of the plant as consequent, this is defined as fuzzy MPC as follows

$$u_i = (S_i^T \bar{Q} S_i + \bar{R})^{-1} S_i Q (w - p_i) \quad (10)$$

where

p_i is a recursive variable that is tuned according to plant timing horizons and inherent time delays (defined in equation (12));
 w are the future set points;
 u_i is the control output;
 Q and R are positive definite weight matrices defined as

$$\bar{Q} = \text{Diag}(Q)$$

$$\bar{R} = \text{Diag}(R)$$

S represents the effect of future outputs and from the integration to antecedent representation of the fuzzy logic system (equation (8)), over N_p and N_c horizons defined by the user

$$S = \begin{bmatrix} S_{N_{p1}} & S_{N_{p1}+1} & \dots & 0 \\ S_{N_{p2}-1} & S_{N_{p1}} & S_{N_{p1}+1} & \\ \vdots & \vdots & \ddots & \\ S_{N_{p2}} & S_{N_{p2}-1} & \dots & S_{N_{p2}-N_c} \end{bmatrix} \quad (11)$$

in which

$$s_j = y_0 \quad \forall j \leq n_d \\ s_j = \sum_{i=1}^{Na} a_i s_{j-i} + \sum_{i=1}^{Nb} B^p u(k-j-n_d+i) + c \\ p_i = \sum_{j=1}^{Na} a_j p_{i-j} + \sum_{j=1}^{Nb} b_j B_j^p u(k-j-n_d+i) + c \quad (12)$$

Figure 6 shows how these horizons take place in time.



Fig. 6 Time horizons with respect to time delays, horizon samples, and k sampling time

3 In Fig. 6, N_a and N_b are the horizon samples, k is the sampling time, l is the related time delay within the sampling time, n_d is the minimum discrete dead-time. In equation (12), the parameters of the plant are presented as a_j and B_i^p where

$$b_j = f(B_j^p)$$

and

$$B_i^p = \int_{t_i}^{t_{i+1}} e^{(a^p - \tau)} d\tau B$$

From the integration to antecedent representation of the fuzzy system (equation (8))

$$\begin{aligned} D_i(y_x, u_{x'}) &= \prod_{j=1}^{N_p} \mu_{ij}(y_x, u_{x'}) \\ &= \prod_{j=1}^{N_p} \exp \left[- \left(\frac{y_x - c_{ij}^y}{\sigma_{ij}^y} \right)^2 - \left(\frac{u_{x'} - c_{ij}^u}{\sigma_{ij}^u} \right)^2 \right] \end{aligned} \quad (13)$$

$$\alpha = \begin{cases} 0 & j > N_p \\ j & 1 \leq j \leq N_p \end{cases} \quad \alpha' = \begin{cases} 0 & 1 \leq j \leq N_p \\ j & j > N_p \end{cases}$$

where

N_p is the number of possible inputs for the fuzzy plant;
 y is the output of the plant;
 u is the plant input.

For the antecedent part of fuzzy control Ω_i

$$\begin{aligned} \Omega_i(y_x, u_{x'}) &= \prod_{j=1}^{N_A} \mu_{ij}(y_x, u_{x'}) \\ &= \prod_{j=1}^{N_A} \exp \left[- \left(\frac{y_x - c_{ij}^y}{\sigma_{ij}^y} \right)^2 - \left(\frac{u_{x'} - c_{ij}^u}{\sigma_{ij}^u} \right)^2 \right] \end{aligned} \quad (14)$$

$$\alpha \begin{cases} 0 & j > N_A \\ j & 1 \leq j \leq N_A \end{cases} \quad \alpha' \begin{cases} 0 & 1 \leq j \leq N_A \\ j & j > N_A \end{cases}$$

where N_A is the number of possible inputs for the fuzzy controller, following that expressed in Fig. 6.

In this case, fault conditions are presented as the results of local time delays more than the actual loss of current measure. Remember that equation (3) and equation (4) are the basis for time delay by using EDF as the scheduling algorithm, presented as

$$3t_s + t_{cm}^{sc} + t_c + t_{cm}^{ca} + t_a < T$$

Thus, the plant representation is given by equation (15) considering time delays

$$x(k+1) = \frac{\sum_{i=1}^N D_i(y_x, u_{x'}) [a_i x(k) + B_i^p u(k)]}{\sum_{i=1}^N D_i(y_x, u_{x'})} \quad (15)$$

where N is the number of rules, and the plant input is defined as considering time delays expressed in equation (14)

$$u(k) = \frac{\sum_{i=1}^N \Omega_i(y_x, u_{x'}) (S_k^T \bar{Q} S_k + \bar{R})^{-1} S_k \bar{Q} (w - p_k)}{\sum_{i=1}^N \Omega_i(y_x, u_{x'})} \quad (16)$$

Substituting in equation (15)

$$x(k+1) = \frac{\sum_{i=1}^N D_i(y_x, u_{x'}) \left(a_i x(k) + B_i^p \frac{\sum_{i=1}^N \Omega_i(y_x, u_{x'}) (S_k^T \bar{Q} S_k + \bar{R})^{-1} S_k \bar{Q} (w - p_k)}{\sum_{i=1}^N \Omega_i(y_x, u_{x'})} \right)}{\sum_{i=1}^N D_i(y_x, u_{x'})} \quad (17)$$

On the other hand, in order to establish valid horizons considering time delays and failures, an MPC strategy is used, and therefore, the cost function in MPC is defined as

$$J = \sum_{i=1}^{N_p} B_i^p (\text{ref}_i - y_i)^2 + \sum_{i=1}^{N_A} \delta_i (u_i)^2 \quad (18)$$

where ref_i and y_i are the reference and output values respectively. This equation can be rewritten as

$$J = \sum_{k=1}^{N_p} B_k^p [\text{ref}_k - Cx(k-1)]^2 + \sum_{k=1}^{N_A} \delta_k (u_k)^2 \quad (19)$$

Considering the variables x and u_i defined in equation (15) and equation (16)

Since the values of \mathbf{Q} , \mathbf{S} , and \mathbf{R} are defined as positive definite matrices in equation (10), it is necessary to obtain the partial derivatives for each variable in order to get the optimal values as:

$$\frac{\partial J}{\partial B_k^p} = 2 \sum_{k=1}^{N_p} B_k^p [\text{ref}_k - Cx(k-1)] \quad (21)$$

$$\frac{\partial J}{\partial \delta_k} = 2 \sum_{k=1}^{N_A} \delta_k (u_k) \quad (22)$$

$$J = \sum_{k=1}^{N_p} B_k^p \left(\text{ref}_k - C \frac{\sum_{i=1}^N D_i(y_{\alpha}, u_{\alpha'}) (a_i x(k-2) + B_i^p u(k-2))}{\sum_{i=1}^N D_i(y_{\alpha}, u_{\alpha'})} \right)^2 + \sum_{k=1}^{N_A} \delta_k \left(\frac{\sum_{i=1}^N \Omega_i(y_{\alpha}, u_{\alpha'}) (S_k^T \bar{Q} S_k + \bar{R})^{-1} S_k \bar{Q} (w - p_k)}{\sum_{i=1}^N \Omega_i(y_{\alpha}, u_{\alpha'})} \right) \quad (20)$$

$$\frac{\partial J}{\partial a_i} = 2C \sum_{k=1}^{N_p} B_k^p \left\{ \text{ref}_k - C \frac{\sum_{i=1}^N D_i(y_{\alpha}, u_{\alpha'}) [a_i x(k-2) + B_i^p u(k-2)]}{\sum_{i=1}^N D_i(y_{\alpha}, u_{\alpha'})} \right\} \left[\frac{\sum_{i=1}^N D_i(y_{\alpha}, u_{\alpha'}) x(k-2)}{\sum_{i=1}^N D_i(y_{\alpha}, u_{\alpha'})} \right] \quad (23)$$

$$\frac{\partial J}{\partial B_i^p} = 2 \sum_{k=1}^{N_p} B_k^p \left\{ \text{ref}_k - C \frac{\sum_{i=1}^N D_i(y_{\alpha}, u_{\alpha'}) [a_i x(k-2) + B_i^p u(k-2)]}{\sum_{i=1}^N D_i(y_{\alpha}, u_{\alpha'})} \right\} \left[\frac{Cu(k-2)}{\sum_{i=1}^N D_i(y_{\alpha}, u_{\alpha'})} \right] \quad (24)$$

$$\frac{\partial J}{\partial D_i} = 2C \sum_{k=1}^{N_p} B_k^p [\text{ref}_k - Cx(k-1)] \left\{ \frac{\sum_{i=1}^N [a_i x(k-2) + B_i^p u(k-2)] - Nx(k-1)}{\sum_{i=1}^N D_i(y_{\alpha}, u_{\alpha'})} \right\} \quad (25)$$

$$\frac{\partial J}{\partial \Omega_i} = 2 \sum_{k=1}^{N_A} \delta_k u(k) \left[\frac{\sum_{i=1}^N (S_k^T \bar{Q} S_k + \bar{R})^{-1} S_k \bar{Q} (w - p_k) - Nu(k)}{\sum_{i=1}^N \Omega_i(y_{\alpha}, u_{\alpha'})} \right] \quad (26)$$

Using equation (13) to obtain the partial derivatives of D_i with respect to c_{ij} and σ_{ij}

$$\frac{\partial D_i}{\partial c_{ij}^y} = -2 \sum_{k=1}^{N_p} \left[\frac{y_x - c_{ik}^y}{(\sigma_{ik}^y)^2} \right] \exp \left[- \left(\frac{y_x - c_{ik}^y}{\sigma_{ik}^y} \right)^2 \right] \prod_{j=1, j \neq k}^{N_p} \exp \left[- \left(\frac{y_x - c_{ij}^y}{\sigma_{ij}^y} \right)^2 - \left(\frac{u_{x'} - c_{ij}^u}{\sigma_{ij}^u} \right)^2 \right] \quad (27)$$

$$\frac{\partial D_i}{\partial c_{ij}^u} = -2 \sum_{k=1}^{N_p} \left[\frac{u_{x'} - c_{ik}^u}{(\sigma_{ik}^u)^2} \right] \exp \left[- \left(\frac{u_{x'} - c_{ik}^u}{\sigma_{ik}^u} \right)^2 \right] \prod_{j=1, j \neq k}^{N_p} \exp \left[- \left(\frac{y_x - c_{ij}^y}{\sigma_{ij}^y} \right)^2 - \left(\frac{u_{x'} - c_{ij}^u}{\sigma_{ij}^u} \right)^2 \right] \quad (28)$$

Analogously, for σ_{ij}^y and σ_{ij}^u

$$\frac{\partial D_i}{\partial \sigma_{ij}^y} = -\frac{1}{2} \sum_{k=1}^{N_p} \frac{(y_x - c_{ik}^y)^2}{(\sigma_{ik}^y)^3} \exp \left[- \left(\frac{y_x - c_{ik}^y}{\sigma_{ik}^y} \right)^2 \right] \prod_{j=1, j \neq k}^{N_p} \exp \left[- \left(\frac{y_x - c_{ij}^y}{\sigma_{ij}^y} \right)^2 - \left(\frac{u_{x'} - c_{ij}^u}{\sigma_{ij}^u} \right)^2 \right] \quad (29)$$

$$\frac{\partial D_i}{\partial \sigma_{ij}^u} = -\frac{1}{2} \sum_{k=1}^{N_p} \frac{(u_{x'} - c_{ik}^u)^2}{(\sigma_{ik}^u)^3} \exp \left[- \left(\frac{u_{x'} - c_{ik}^u}{\sigma_{ik}^u} \right)^2 \right] \prod_{j=1, j \neq k}^{N_p} \exp \left[- \left(\frac{y_x - c_{ij}^y}{\sigma_{ij}^y} \right)^2 - \left(\frac{u_{x'} - c_{ij}^u}{\sigma_{ij}^u} \right)^2 \right] \quad (30)$$

Applying the previous results, and using equation (25)

$$\begin{aligned} \frac{\partial J}{\partial c_{ij}^y} &= \frac{\partial J}{\partial D_i} \frac{\partial D_i}{\partial c_{ij}^y} = 2C \sum_{k=1}^{N_p} B_k^p [\text{ref}_k - Cx(k-1)] \left\{ \frac{\sum_{i=1}^N [a_i x(k-2) + B_i^p u(k-2)] - Nx(k-1)}{\sum_{i=1}^N D_i(y_x, u_{x'})} \right\} \\ &\times \left\{ -2 \sum_{k=1}^{N_p} \left[\frac{y_x - c_{ik}^y}{(\sigma_{ik}^y)^2} \right] \exp \left[- \left(\frac{y_x - c_{ik}^y}{\sigma_{ik}^y} \right)^2 \right] \prod_{j=1, j \neq k}^{N_p} \exp \left[- \left(\frac{y_x - c_{ij}^y}{\sigma_{ij}^y} \right)^2 - \left(\frac{u_{x'} - c_{ij}^u}{\sigma_{ij}^u} \right)^2 \right] \right\} \quad (31) \end{aligned}$$

and applying the same for c_{ij}^u

$$\begin{aligned} \frac{\partial J}{\partial c_{ij}^u} &= \frac{\partial J}{\partial D_i} \frac{\partial D_i}{\partial c_{ij}^u} = 2C \sum_{k=1}^{N_p} B_k^p [\text{ref}_k - Cx(k-1)] \left\{ \frac{\sum_{i=1}^N [a_i x(k-2) + B_i^p u(k-2)] - Nx(k-1)}{\sum_{i=1}^N D_i(y_x, u_{x'})} \right\} \\ &\times \left\{ -2 \sum_{k=1}^{N_p} \left[\frac{u_{x'} - c_{ik}^u}{(\sigma_{ik}^u)^2} \right] \exp \left[- \left(\frac{u_{x'} - c_{ik}^u}{\sigma_{ik}^u} \right)^2 \right] \prod_{j=1, j \neq k}^{N_p} \exp \left[- \left(\frac{y_x - c_{ij}^y}{\sigma_{ij}^y} \right)^2 - \left(\frac{u_{x'} - c_{ij}^u}{\sigma_{ij}^u} \right)^2 \right] \right\} \quad (32) \end{aligned}$$

Analogously for σ_{ij}^y and σ_{ij}^u

$$\begin{aligned} \frac{\partial J}{\partial \sigma_{ij}^y} &= \frac{\partial J}{\partial D_i} \frac{\partial D_i}{\partial \sigma_{ij}^y} = 2C \sum_{k=1}^{N_p} B_k^p [\text{ref}_k - Cx(k-1)] \left\{ \frac{\sum_{i=1}^N [a_i x(k-2) + B_i^p u(k-2)] - Nx(k-1)}{\sum_{i=1}^N D_i(y_x, u_{x'})} \right\} \\ &\times \left\{ -\frac{1}{2} \sum_{k=1}^{N_p} \frac{(y_x - c_{ik}^y)^2}{(\sigma_{ik}^y)^3} \exp \left[- \left(\frac{y_x - c_{ik}^y}{\sigma_{ik}^y} \right)^2 \right] \prod_{j=1, j \neq k}^{N_p} \exp \left[- \left(\frac{y_x - c_{ij}^y}{\sigma_{ij}^y} \right)^2 - \left(\frac{u_{x'} - c_{ij}^u}{\sigma_{ij}^u} \right)^2 \right] \right\} \quad (33) \end{aligned}$$

$$\frac{\partial J}{\partial \sigma_{ij}^u} = \frac{\partial J}{\partial D_i} \frac{\partial D_i}{\partial \sigma_{ij}^u} = 2C \sum_{k=1}^{N_p} B_k^p [\text{ref}_k - Cx(k-1)] \left\{ \frac{\sum_{i=1}^N [a_i x(k-2) + B_i^p u(k-2)] - Nx(k-1)}{\sum_{i=1}^N D_i(y_z, u_{x'})} \right\} \times \left\{ -\frac{1}{2} \sum_{k=1}^{N_p} \frac{(u_{x'} - c_{ik}^u)^2}{(\sigma_{ik}^u)^3} \exp \left[-\left(\frac{u_{x'} - c_{ik}^u}{\sigma_{ik}^u} \right)^2 \right] \prod_{j=1, j \neq k}^{N_p} \exp \left[-\left(\frac{y_z - c_{ij}^y}{\sigma_{ij}^y} \right)^2 - \left(\frac{u_{x'} - c_{ij}^u}{\sigma_{ij}^u} \right)^2 \right] \right\} \quad (34)$$

A similar procedure is used to obtain the partial derivatives with respect to c_{ij} and σ_{ij} , using equation (14). The optimization procedures of δ , Q , and R are left to the use of this multivariable optimization procedure, since these are design variables.

4 RESULTS

Using this implementation, several experiments are carried out, the results of which are presented in terms of fault presence and its related fault tolerance strategy to overcome system lack of performance regarding a horizon. How the system responds to the fault tolerance strategy is presented as follows, showing the error response from different separation values between membership functions, according to Table 2. The experimental set-up consists of two light sensors connected through two microcontrollers and CANBUS, one light sensor connected to a Q4 analogue-to-digital (A/D) card, one actuator connected to a 612 A/D card; each of the elements has a consumption delay of 1 ms.

Figure 7 shows fault-free scenarios for 10 per cent and 15 per cent of this separation between membership functions, as presented in reference [11]. Faults refer to light capture that detects current movement of the ball of the magnetic levitation case study. Both faults are local deviations of current responses from light sensors. These are not catastrophic faults, but only partial deviation from current measurements. These faults are presented locally, and within a time frame bigger than the sampling time.

For both fault scenarios, the response of the systems is shown in Table 3. Figure 8 shows the error response for each fault scenario, when switching from one sensor to another, using the separation of

Table 2 Fault-free scenario for different per cent of separation values between membership functions

Separation (%)	Integral of the error
10	0.4400
15	0.4495

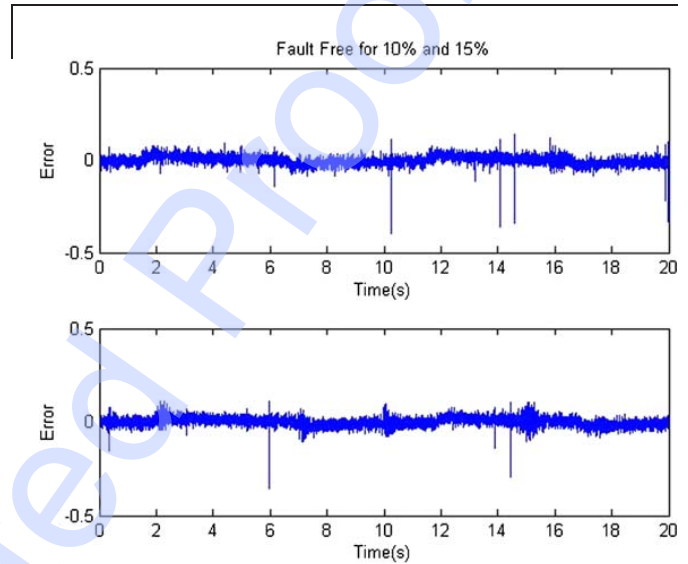


Fig. 7 Error response from fault-free scenario

Table 3 The integral of the error for the fault scenario

Separation (%)	Integral of the error
10	0.5003
15	0.4567

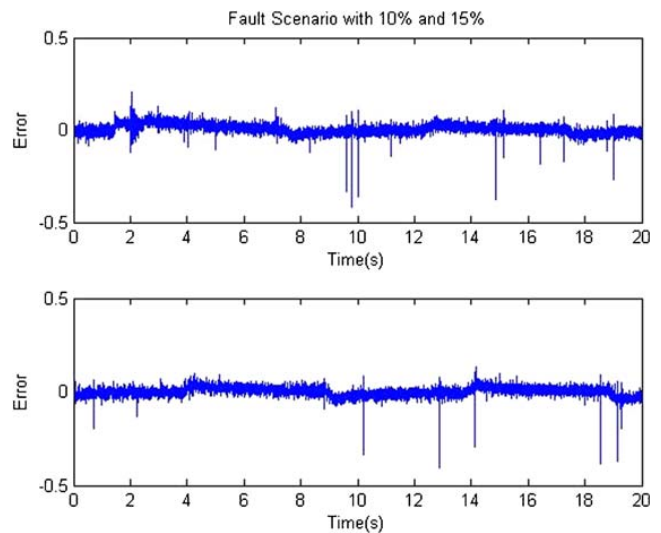


Fig. 8 Error response from fault scenario 1

10 per cent and 15 per cent. Figure 9 shows current response from the error signal considering the first fault scenario. Alternatively, Fig. 10 presents the response of the system compared with the current set point.

This last example presents the reconfiguration control strategy based on the decision-maker module and the related fuzzy MPC. Active switching control is performed using a fuzzy TKS approach when a local fault appears, and fault-tolerant node is activated. Such a reconfiguration control strategy is feasible owing to the knowledge about time delays. Notice that the consumption time of the reconfiguration control strategy is neglected, since it is considered to be part of control performance. It is obvious that fault

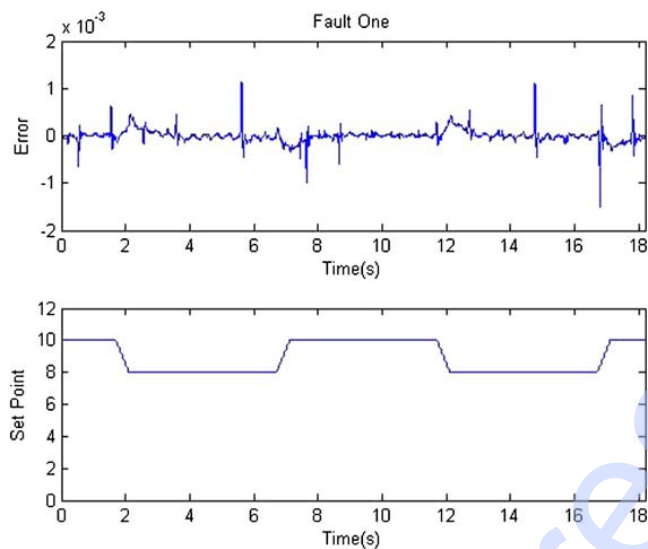


Fig. 9 Error response for first fault scenario considering current set point

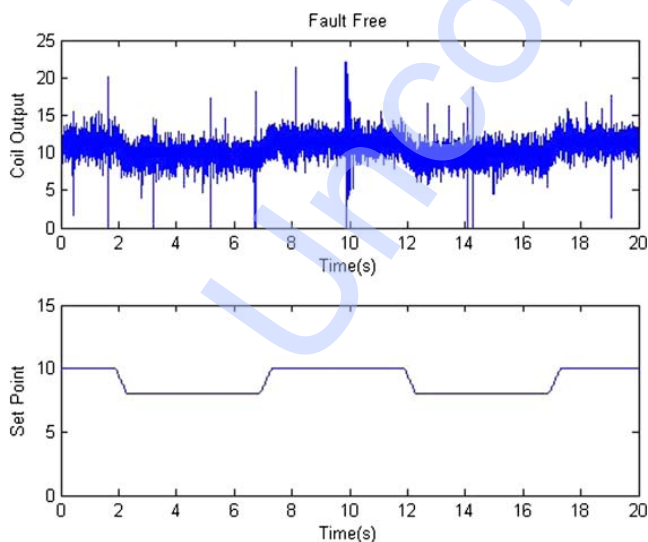


Fig. 10 Set point and system response from case study

presence is measurable: if a local fault cannot be detected, the strategy becomes useless. Alternatively, local time delay management refers to the use of a quasi-dynamic scheduler to propose dynamic reconfiguration, based on current system behaviour rather than predefined scenarios. Error responses present noise conditions that are inherent to system response.

To define the communication network performance, the use of xPC Target is necessary. Such a network implementation uses message transactions that are implemented in the real-time workshop toolbox from MATLAB [17]. For the case study, two types of computer network are used: CANbus and Ethernet. Both networks present no further time delay difference because network size is kept quite small. Actual set-up of both computer networks is presented in Table 4.

5 CONCLUDING REMARKS

The present paper presents an approach for integrating two techniques in order to perform reconfiguration: structural reconfiguration and control reconfiguration. These two techniques are applied in cascade. Although there is no formal verification for following this sequence, it has been adopted because structural reconfiguration provides stable conditions for control reconfiguration. Moreover, the use of a real-time scheduling algorithm to approve or disapprove changes in the behaviour of a computer network allows bounding time delays during a specific time frame. This local time delay allows the design of a control law that is capable of coping with new conditions.

Preliminary results show that the proposed reconfiguration control strategy is feasible as long as the use of a wide enough horizon predetermines which control law is adequate. This is accomplished by the composition of two algorithms: one responsible for structural reconfiguration (and implemented here as ART-2A) and the second responsible for control reconfiguration (here based on fuzzy TKS and MPC). The importance of this approach is that control conditions are strictly bounded to a certain

Table 4 Current conditions on computer network

	CANBUS	ETHERNET
Bandwidth	1 Mbits/s	10 Mbits/s
Number of nodes	4	3
Bus loading	64 Bytes/node (there are no more nodes transmitting on this network)	1 KByte/node (there are no more nodes transmitting on this network)

response. Future work will be related to integrating dynamic scheduling algorithms and a formal stability probe for this implementation.

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