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Design of Hybrid Fault Tolerance Control for LPV System

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ABSTRACT

Modern technological devices rely on sophisticated control systems to meet increased performance requirements. For such systems, the consequences of faults in system components can be catastrophic. Therefore it is necessary to design control systems which are capable of tolerating potential faults in the systems to obtain the desired performance. The paper presents the approach for fault tolerant control (FTC) based on model reference control (MRAC) with artificial neural network (ANN) controller to analyze the ability of coupled tank linear parameter varying (LPV) system to accommodate the faults. The performance of the proposed FTC scheme is tested using a Coupled-Tank system which is used as a test bed with two different types of faults with different magnitudes and with different operating points. From the simulation results it has been proved that the proposed controller is fault tolerant and makes the system to achieve quick steady state stability against the various types of faults.

Keywords

Fault Tolerant Control(FTC), Artificial Neural Network(ANN), Model Reference Adaptive control(MRAC), Linear Parameter Varying System.

1. INTRODUCTION

In a modern technological system includes sophisticated control system such as aircrafts, spacecrafts, nuclear power plants, and chemical plants processing hazardous materials, the consequences of a minor fault in a system component can be catastrophic. Therefore, the demand on reliability, safety and fault tolerance is generally high. It is necessary to design control systems which are capable of tolerating potential faults in these systems in order to improve the reliability and availability while providing a desirable performance. These types of control systems are often known as fault tolerant control systems (FTCS). More precisely, FTCS are control systems which possess the ability to accommodate component failures automatically. They are capable of maintaining overall system stability and acceptable performance in the event of various types of faults [1]-[5]. More recently, the fault-tolerant control problem has begun to draw more and more attention in a wider range among industrial and academic communities, due to increased safety and reliability demands beyond the conventional control system can offer. The main goal in a fault-tolerant control system is to design a controller with a suitable structure to achieve stability and satisfactory performance, not only when all control components are functioning normally, but also in cases when there are malfunctions in sensors, actuators, or other system components. Fault-tolerant control scheme may be categorized into two broad categories: passive fault-tolerant control scheme (PFTCS) and active fault tolerant control scheme (AFTCS). In PFTCS, controllers are fixed and are designed to be robust against a class of presumed faults. This approach neither needs fault detection and diagnosis (FDD) nor controller reconfiguration, but has limited fault-tolerant capabilities. On the other hand, AFTCS react to component failures actively by reconfiguring control actions so that the plant stability and acceptable performance of the entire system can be maintained [5]-[8].

However the control methods discussed in the earlier research papers handle only linear time varying system. For the system encountered with nonlinear behaviour with more dynamics offers the theory of linear parameter varying systems. This class of systems is particularly suited to deal with processes that operate in varying operating regions [9]-[11]. The main intention of this work is to develop a passive structure of fault tolerant control to deal with two different type of faults such as abrupt and gradual faults of actuators and sensors of processes represented by LPV models. A neural network based MRAC controller is chosen as a FTC because it guarantees asymptotic output tracking, it has a direct physical interpretation and it is easy to implement. A coupled-tank system is used to demonstrate the performance of the proposed scheme.

2. CONTROLLER DESIGN

2.1 Process description

The linear parameter varying (LPV) systems depend on a set of variant parameters over time [10]-[11]. These systems can be represented in state space (continuous or discrete). The continuous representation of an LPV system is represented in eqns. (1) and (2),

$$\dot{x} = A(\varphi(t))x + B(\varphi(t))u \tag{1}$$

$$y = C(\varphi(t))x + D(\varphi(t))u \quad (2)$$

$x \in R^n$ represents the state space vector, $y \in R^m$ represents the measurement or output vector, $u \in R^p$ represents the control input vector and φ represents the parameters variation over time. There are many methods for LPV modeling such as Jacobian linearization method, state transformation method, substitution function method, least square estimation and polynomial fitting technique. The main objective of these methodologies is to adapt nonlinearity of the system in any variable in order to get the LPV system.

2.2 Mathematical modeling

The coupled tank system, shown in Fig. 1, is modeled as LPV system [11]. The coupled-tank process is composed of two cylindrical tanks, an upper tank (tank1) and a lower tank (tank2). A pump is used to thrust water from the water reservoir to tank1 and the outflow of tank1 flows through tank2 to the water reservoir. Pressure sensors located at the bottom of each tank are used to measure the water levels in the tanks.

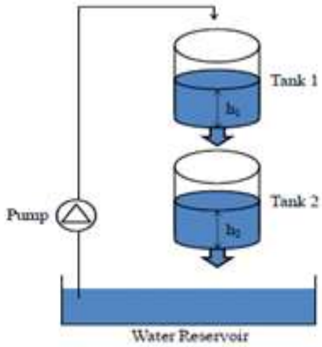

Fig 1: Coupled Tank System

The dynamic equations for the liquid level in the two tanks are derived as follows. The time rate of change of liquid level in each tank is given as in equation(3) and is expressed as cm/s.

$$\dot{h}_i(t) = \frac{1}{A_i}\left(F_i^{in}(t) - F_i^{out}(t)\right),\ i = 1,2 \quad (3)$$

where h_i, A_i, F_{iin} and F_{iout} are the liquid level, cross-sectional area, inflow rate and outflow rate respectively for the tank. The inflow rate into tank1 is given in equation(4) and is expressed as cm^3/s,

$$F_i^{in}(t) = k_p v_p(t) \quad (4)$$

where k_p is the pump constant and v_p is the voltage applied to the pump.

In addition, using Bernoulli's law for flow through small orifices, the outflow velocity from the orifice at the bottom of each tank is represented in equation(5).

$$v_i^{out}(t) = \sqrt{2gh_i(t)},\ i = 1,2 \quad (5)$$

where g is the gravitational acceleration. Then, the outflow rate for each tank is given in equation (6),

$$F_i^{out}(t) = a_i\sqrt{2gh_i(t)},\ \mathrm{i} = 1,2 \quad (6)$$

where a_i denotes the cross-sectional area of the outflow orifice at the bottom of the tank. Finally for the two-tank liquid level system shown the inflow rate of the tank2 is equal to the outflow rate of tank1 and it is given in equation(7),

$$F_2^{in}(t) = F_1^{out}(t) \quad (7)$$

Thus by using the equations(3)-(7), the dynamic equations for the liquid level in the two tanks are described[11] as given in equations(8) and (9).

$$\dot{\mathrm{h}}_1(\mathrm{t}) = -\frac{\mathrm{a}_1}{\mathrm{A}_1}\sqrt{2\mathrm{gh}_1(\mathrm{t})} + \mathrm{k_p v_p(t)} \quad (8)$$

$$\dot{h}_2(t) = \frac{a_1}{A_2}\sqrt{2gh_1(t)} - \frac{a_2}{A_2}\sqrt{2gh_2(t)}$$
(9)

The output equation is given by equation (10),

$$y(t) = h_2(t)$$
(10)

An LPV model of the coupled-tank process is computed using a standard polynomial fitting technique that approximate $\sqrt{h_i}$ for 0≤ h_i ≤30 with $\varphi_i h_i$, where

$$\varphi_i = \alpha_4 h_i^4 + \alpha_3 h_i^3 + \alpha_2 h_i^2 + \alpha_1 h_i^1 + \alpha_0$$
(11)

The variables of LPV model are shown in Table 1.

The parameters are bounded with the following values

$$0 \le \varphi_1 \le 30$$

$$0 \le \varphi_2 \le 30$$

Thus the state space model becomes

$$\dot{x} = \begin{bmatrix} -0.5085\varphi_1 & 0 \\ 0.5085\varphi_1 & -0.5085\varphi_2 \end{bmatrix} (\varphi(t))x + \begin{bmatrix} 0.2127 \\ 0 \end{bmatrix} u$$

$$Y = [0 \quad 1]x$$

Table 1. LPV Model Variables

Variable	Definition	Value
h_1	Water level of tank 1	-
h_2	Water level of tank 2	-
A_1	Cross- sectional area of tank 1	15.5179 cm^2
A_2	Cross- sectional area of tank 2	15.5179 cm^2
a_1	Cross- sectional area of the outflow orifice of tank 1	0.1781 cm^2
a_2	Cross- sectional area of the outflow orifice of tank 2	0.1781 cm^2
v_p	Pump voltage	-
k_p	Pump gain	3.3 cm^3/V s
g	Gravitational constant	981 cm/s^2
α_4	Approximation constant	2.981 x 10^{-7}
α_3	Approximation constant	-3.659 x 10^{-5}
α_2	Approximation constant	1.73 x 10^{-3}
α_1	Approximation constant	-4.036 x 10^{-2}
α_0	Approximation constant	0.583

2.3 Adaptive controller design

The MRAC implements a closed loop controller where the adaptation mechanism adjusts the controller parameters to match the process output with the reference model output. The reference model is specified as the ideal model behaviour that the system is expected to follow. This type of controller behaves as a closed loop controller because the actuating error signal is fed to the controller in order to reduce the error to achieve the desired output value. The controller error is calculated as given in equation (12).

$$e = y - y_m$$
(12)

where y is the process output and y_m is the reference output.

To reduce the error, a cost function used is shown in equation (13).

$$J(\theta) = \frac{1}{2}\, e^2(\theta)$$
(13)

where θ is the adaptive parameter inside the controller.

The cost function can be minimized if the parameters change in the negative direction of the gradient *J*, this is called as gradient descent method and is represented by equation (14).

$$\frac{d\theta}{dt} = -\gamma\frac{\partial J}{\partial\theta} = -\gamma e\frac{\partial e}{\partial\theta} \tag{14}$$

where γ is the speed of learning.

The implemented MRAC is a second order system and has two adaptation parameters: adaptive feed forward gain (θ_1) and adaptive feedback gain (θ_2). These parameters will be updated in equations (15) and (16) to follow the reference model

$$\frac{d\theta_1}{dt} = -\gamma\frac{\partial e}{\partial\theta_1} = -\gamma\left(\frac{a_{1m}s + a_{0m}}{s^2 + a_{1m}s + a_{0m}}u_c\right)e \tag{15}$$

$$\frac{d\theta_2}{dt} = -\gamma\frac{\partial e}{\partial\theta_2} = \gamma\left(\frac{a_{1m}s + a_{0m}}{s^2 + a_{1m}s + a_{0m}}y_{plant}\right)e \tag{16}$$

The state-space LPV model is transformed to a continuous version

$$G_{LPV}(s) = C(sI - A)^{-1}B + D$$

$$G_{LPV}(s) = \begin{bmatrix}0 & 1\end{bmatrix} \times \left(\begin{bmatrix}s & 0\\0 & s\end{bmatrix} - \begin{bmatrix}-0.5085\varphi_1 & 0\\0.5085\varphi_1 & -0.5085\varphi_2\end{bmatrix}^{-1}\right)\begin{bmatrix}0.2127\\0\end{bmatrix}$$

$$G_{LPV}(s) = \frac{0.108158\varphi_1}{(s+0.5085\varphi_2)(s+0.5085\varphi_1)}$$

$$G_{LPV}(s) = \frac{0.108158\varphi_1}{s^2+0.5085(\varphi_1+\varphi_2)s+0.258572\varphi_1\varphi_2} \tag{17}$$

The reference model is given in equation (17). The process model is the same as reference model whenever there are no faults. The adaptive feed-forward update rule *θ1* is given in equation (18)

$$\frac{d\theta_1}{dt} = -\gamma\frac{\partial e}{\partial\theta_1}e = -\gamma\left(\frac{0.5085(\varphi_1+\varphi_2)s+0.258572\varphi_1\varphi_2}{s^2+0.5085(\varphi_1+\varphi_2)s+0.258572\varphi_1\varphi_2}\right)e \tag{18}$$

The adaptive feedback update rule *θ2* is

$$\frac{d\theta_2}{dt} = -\gamma\frac{\partial e}{\partial\theta_2}e = \gamma\left(\frac{0.5085(\varphi_1+\varphi_2)s+0.258572\varphi_1\varphi_2}{s^2+0.5085(\varphi_1+\varphi_2)s+0.258572\varphi_1\varphi_2}y\right)e \tag{19}$$

The schematic diagram of the proposed work is shown in Fig. 2. The error factor goes as an input into the neural network whose function is to minimize the error. The gain values get adjusted in the process of error reduction.

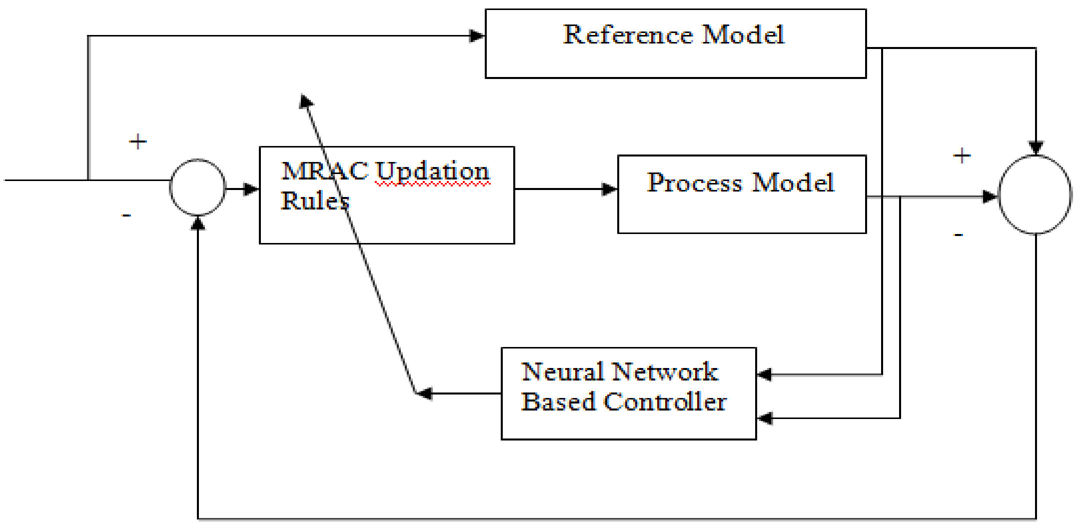

Fig 2: Schematic representation of the FTC based on MRAC-ANN

The final closed responses employing the conventional MRAC design gives an error (offset) in comparison with the reference set point. The error can be minimised by using mulilayer perceptron model based on back propagation algorithm with three layers. The activation function at input layer is linear while at the hidden and output layer is logistic function.

3. SIMULATION RESULTS

The proposed work is tested in MATLAB and the results were simulated for two different types of faults such as abrupt and gradual faults. Abrupt faults in actuators represent, a pump stuck for instance or in sensors a constant bias in measurement. A gradual fault could be a progressive loss of electrical power in pump, and a drift in the measurement for sensors. For the proposed controller both the fault conditions were tested. The response of the system with operating conditions $\varphi_1 = 0.3$ and $\varphi_2 = 0.4$ and without any faults is illustrated in Fig. 3.

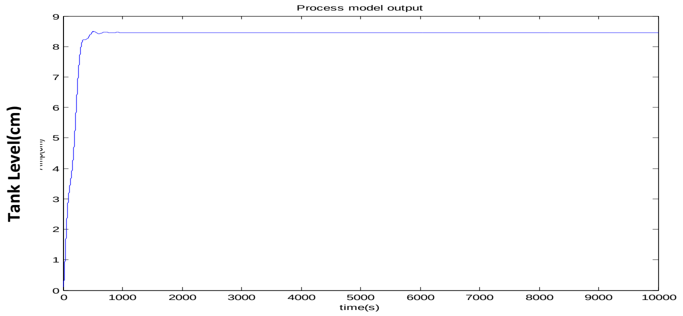

Fig 3: Process model output for fault-free case

3.1 Abrupt fault

The sensor fault of magnitude f_s =6e-2 is introduced at 3000th instant and the actuator fault of magnitude f_a =6e-1 is introduced at 7000th instant. The controller accommodates the faults quickly and the corresponding response of the process model is shown in Fig. 4. It can be observed that the before the fault occurrence, the water level in tank was 8 cm and after the fault occurrence it abruptly decreases to 4 cm. That is 50% reduction due to sensor fault. With the help of proposed controller, instantly the fault is detected by the system and behaved normally within few seconds. During actuator fault, the system produces more oscillations, but the controller suppresses the oscillations and achieves the faster steady state value. The output shown in Fig.4 gives an offset. When the MRAC is combined with neural network, the offset gets decreased.The perfomance of the neural network for training and test data for abrupt fault condition is shown in Fig. 5.

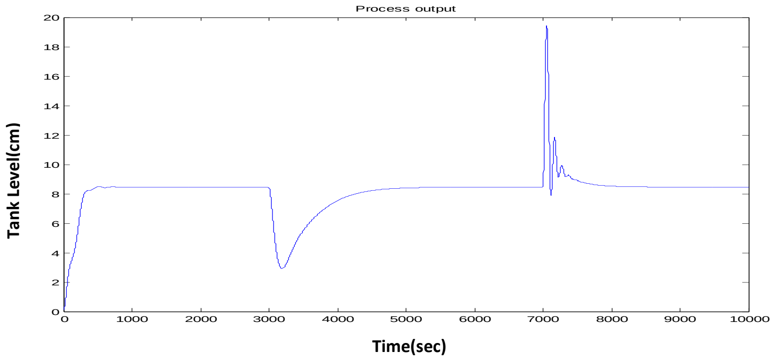

Fig 4: Process model output for abrupt fault case with MRAC-ANN

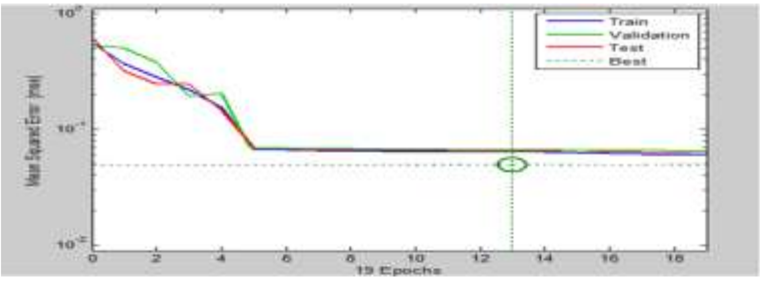

Fig 5: Neural Network output for abrupt fault condition

3.2 Gradual fault

The performance degradation also occurs in the system due to faults in actuator dynamics. The sensor fault of magnitude f_s =6e-2 is introduced at 3000th instant and the actuator fault of magnitude f_a =6e-1 is introduced at 7000th instant. Since the fault is gradual, the oscillations prolongs for longer period of time. The amplitude of oscillation is very high compared to oscillations produced by abrupt faults. Even though the fault magnitude is high the MRAC suppresses the fault and achieves the faster steady state value. The process model output for gradual fault case is shown in Fig. 6. It gives an offset of 0.5. When the MRAC is combined with neural network, the offset gets decreased.

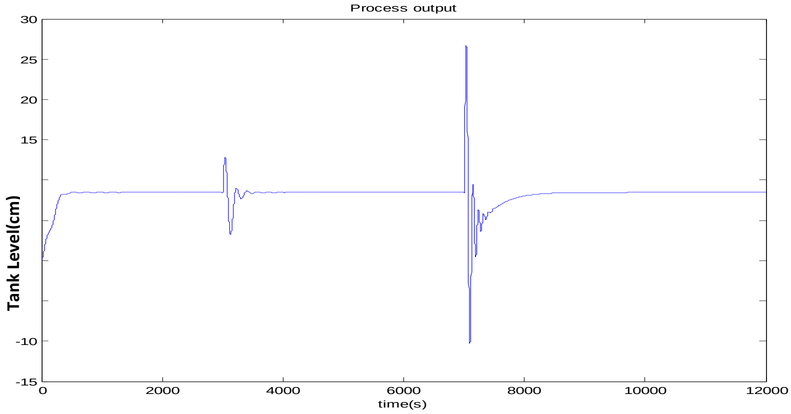

Fig 6: Process model output for gradual fault case with MRAC-ANN

Time(sec)

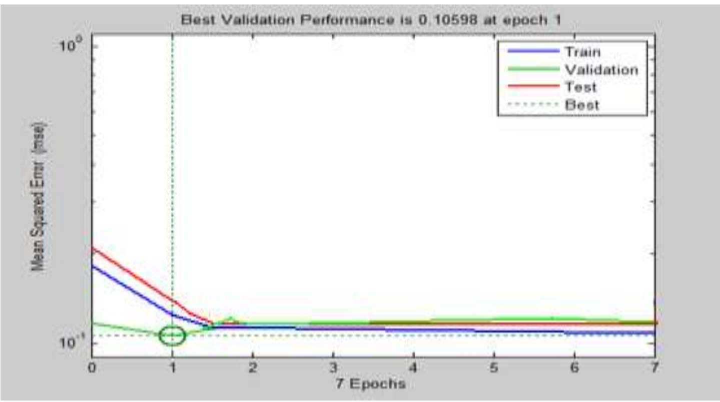

Fig 7: Neural Network output for gradual fault condition

Neural network performance for training and test data for gradual fault condition is shown in Fig. 7. The training is stopped after 19 iterations because the test set error and the validation set error have similar characteristics. Table 2, demonstrates the types of faults and the controller action corresponding to the magnitude of faults for the range of operating points.

Table 2. Types of faults and controller actions

Sensor Faults		Actuator Faults	
Abrupt Faults	**Gradual Faults**	**Abrupt Faults**	**Gradual Faults**
0<f<1 Fault Tolerant	+/-0<f<+/-1 Fault Tolerant	0<f<6 Fault Tolerant	+/-0<f<+/-6 Fault Tolerant
f>1 Unstable	f>+/-1 Unstable	f>6 Unstable	f>+/-6 Unstable

For both abrupt and gradual fault conditions, the proposed FTC is robust for the maximum of 10% deviation in sensor from its nominal value and 60% deviation in the actuator from its nominal value. When the fault limits exceed the specified threshold, the system becomes unstable.

4. CONCLUSION

The hybrid fault tolerant control design effectively combined the MRAC and Neural network to tolerate both abrupt and gradual faults of different magnitudes occuring at different time instances. When compared to conventional MRAC, this hybrid controller minimises the offset and hence assures improved performance. From the simulation results, it has been observed that, for the range of fault size on both abrupt and gradual fault conditions, the proposed FTC is robust, fault tolerant or unstable against the fault.

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