

# Adaptive Controller Using Dynamic Safety Margin for Hybrid Laboratory Plant

M. Abd-Elgeliel and E. Badreddin

[elgeliel@ti.uni-mannheim.de](mailto:elgeliel@ti.uni-mannheim.de), [Badreddin@ti.uni-mannheim.de](mailto:Badreddin@ti.uni-mannheim.de)

Automation Lab., University of Mannheim, Germany

**Abstract-** A large disturbance or model parameters variation in controlled system may lead to system failure and decrease system safety. Adapting controller parameters is essential to compensate the system disturbance or model uncertainties. In this work, controller parameters have been adapted based on the Dynamic Safety Margin (DSM) index [1] to increase the system safety during different operation condition. Fuzzy controller is used to supervise DSM and adapts the controller parameters also predictive controller based on DSM is discussed. The real time implementation, for adaptive controller based on DSM, is tested on a hybrid laboratory plant.

## I. INTRODUCTION

Most of the industrial plants have a hybrid characteristic. In the last decade, many efforts have been carried out in order to develop theoretical tools to deal with hybrid system [2]-[4]. In this work, we introduce adaptation method to readjust the controller parameters in order to improve performance, specially systems with hybrid characteristic.

Adjusting the controller parameters to overcome the disturbance effects and model uncertainties are necessary to maintain accepted system performance. Adaptive controller and robust controller are the main tools used to disturbance effect reduction [5],[6]. Most of the adaptive control algorithms adjust the controller according to the difference between the actual output and the desired output [6]. In this work, we tune the controller parameters based on how far the system current states from the set of the safe operation region. The distance between the system state and the safe operation boundaries is defined as Dynamic Safety Margin (DSM) [1]. The DSM value is directed i.e. it has + or - sign. Negative sign means that the system state lies outside the safe operation region and positive otherwise. The adapting mechanism adapts the controller parameters in case of negative DSM to recover the system states inside the safety region. Adjusting controller or adapting controller parameters based on DSM are mainly important in fault tolerant control (FTC) [15]-[16] system to insure the system safety and recover the system performance in the presense of fault. Two adapting controller methods are tested here to readjust the proportional gain of PID controller for the laboratory process, which has been

exposed to external disturbance. The first one defines the adapted parameter as a linear function of DSM and the other use fuzzy controller [7],[8] to readjust the gain. Predictive controller [13] has been known as an efficient tool for the control of many practical systems, due to its considerable degree of performance and robustness. Introducing DSM in predictive control design is important to adapt the controller in order to guarantee the safe operation. Design predictive controller based on DSM is tested in this work.

The outline of this paper is as follows. The plant description and system configuration are introduced in Section II. The idea of safety margin and adapting mechanism are discussed in Section III. Section IV shows the system experiment and results. The conclusion is discussed in the last section.

## II. PLANT DESCRIPTION AND REAL-TIME ARCHITECTURE.

The process control laboratory plant uses standard industrial components, which introduces more realism and robustness into the experiments with control application. The complete description of the laboratory plant can be found in [9]. Fig. 1 shows an overview of the set-up. The plant consists essentially of two tanks of 100 l, a sump of 300 l, a pump (11kW), a heat exchanger, three control valves, on/off valves, 6 temperature sensors, 3 level sensors, 3 pressure sensors, and one flow rate sensor. All these components are industrial ones. Valves are actuated by compressed air and all signals sensor/actuator and the computer systems are transmitted by using 4-20 mA standards. The plant works as follows: water is pumped from the sump and it circulates round the plant following a selected (by on/off valves) path to come back to the sump closing the loop. The pump works at a constant rotational speed and the flow rate is fixed by mean of an electric modulating valve. Manual/automatic valves are used to change parameters and select different operating points. The schematic diagram is shown in Fig. 2.

For this work, the plant was configured (Fig. 2) where the level in the left tank ( $h$ ) was selected as controlled variable and the control signal  $u$  was applied to the left

control valve. On the right tank, the valve was selected at a variable opening to simulate different leakage of the left tank.



Fig. 1 Overview of the laboratory plant

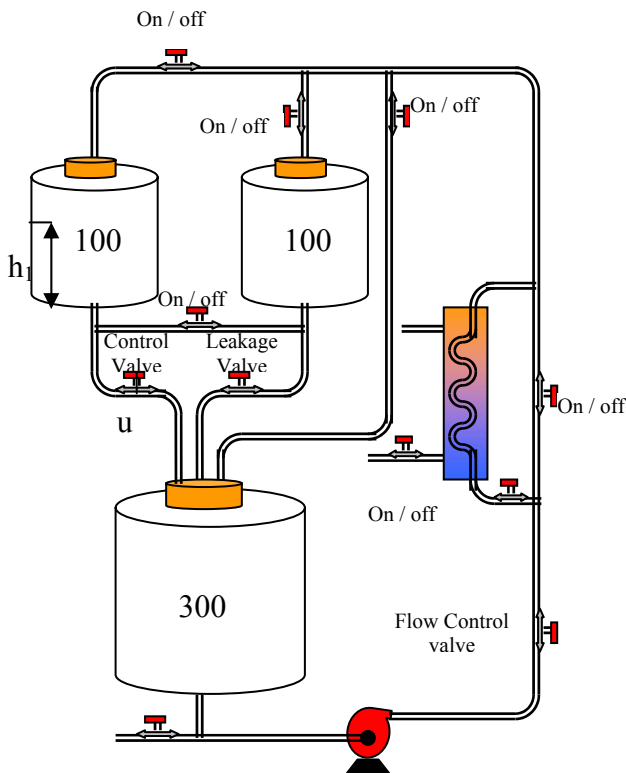


Fig. 2 Schematic diagram of Two Tank system

The interconnecting valve was commanded according to the following criteria: the valve become off, before the level in the left tank reaches the desired value and on after that. The first instance, the plant has the behaviour of a one-tank system until the level of the left tank reach a certain limit and two-tank system after the interconnected valve is opened.

The input flow is set to 1 l/sec and the level controlled through the outflow control valve. The discrete linear state space models of one-tank Table 1, when the interconnected valve is close, and two-tank system Table 2, interconnected valve is open, at sampling rate 0.1 sec of the system are [10]:

Table 1: Linear state-space model of one-tank-system

<b>A</b>	<b>B</b>
$\begin{bmatrix} 0.999741 & -6.94 e-5 \\ 0 & 0.740818 \end{bmatrix}$	$\begin{bmatrix} -1.0932 e-5 \\ 0.25918177 \end{bmatrix}$
<b>C</b>	<b>D</b>
$\begin{bmatrix} 1 & 0 \end{bmatrix}$	$\begin{bmatrix} 0 \end{bmatrix}$

Table 2: Linear state-space model of the two-tank-system

<b>A</b>	<b>B</b>
$\begin{bmatrix} 0.9748 & 0.0019 & -0.0146 \\ -0.1616 & -0.2104 & 0.5555 \\ -2.4323 & -1.1408 & 0.2307 \end{bmatrix}$	$\begin{bmatrix} -0.0004 \\ -0.0105 \\ -0.0173 \end{bmatrix}$
<b>C</b>	<b>D</b>
$\begin{bmatrix} 1 & 0 & 0 \end{bmatrix}$	$\begin{bmatrix} 0 \end{bmatrix}$

The controlled variable in both cases, one and two tank, is the level in the left tank while the right tank is free.

The real time system configuration consists of two parts

**System Hardware:** Two computers in Host/Target configuration to implement real-time control system. The host is a computer without real time requirements, in which the develop environment, data visualization and control panel in the form of a Graphical User Interface (GUI) reside (windows operatin system). The real time system run on the target (QNX operating system [11]).

**Software:** Integration with Matlab/simulink and real-Time Workshop (RTW). RTW generates C codes directly from the suimulink model and construct a file that can be excuted in real time computer (target).

For more detail see [8] and [9]

### III. DYNAMIC SAFETY MARGIN AND ADAPTATIVE MECHANISM

The idea of DSM index is introduced in [1]. Briefly to explain the idea, consider that the safe operation region  $\Phi \subseteq X$  for some of the system states in state space can be given by a set of  $\phi(\mathbf{x}) \leq 0$  while  $\phi(\mathbf{x}) > 0$  indicates unsafe operation (Fig. 3) and we shall further assume that the system is stable -in the sense of Lyapunov- with its stability

region fully contained in the safe region. Starting with the initial condition  $\mathbf{x}_0$ , the system trajectory will evolve to the operating point  $\mathbf{x}_s$  traversing the state space with varying distance to the safety boundary. DSM in this case is defined as the shortest distance,  $\delta(t)$ , between the system state of interest and a predefined boundary  $\phi(\mathbf{x})=0$  in this subspace of the state variables. Most of the time the variables are not independent of one another and none of them adequately defines the system safety by itself i.e. the individual state limits are not necessary the boundary limits [12].

In general for  $\mathbf{x} \in X$ ,  $\phi: \mathbb{R}^m \rightarrow \mathbb{R}$ , the safe-operation region  $\Phi \subseteq X$  is defined by a set of inequalities,

$$\Phi = \{\phi_i(x) < 0 | i=1, \dots, q\} \quad (1)$$

and DSM is given

$$\begin{aligned} \delta^*(t) &= \min_i \{\delta_i(t)\} \\ \delta_i(t) &= s(t) \cdot \|\phi_i(\mathbf{x}) - \mathbf{x}\|_{\min}, \mathbf{x} = (x_1, x_2, \dots, x_m) \end{aligned} \quad (2)$$

$$\text{Where } s(t) = \begin{cases} +1 & \text{if } \mathbf{x} \text{ inside the safe operation region} \\ -1 & \text{if } \mathbf{x} \text{ outside the safe operation region} \end{cases}$$

$$\|\cdot\|_{\min} \triangleq \text{shortest distance from } \mathbf{x}(t) \text{ to } \phi$$

$q$  is the number of defined inequalities and  $m$  the number of state variables relevant to safety. Notice that  $m \leq n$  the dimension of the state-space.

In most cases, the safe operation region can be defined by a set of linear inequalities ( $\phi \leq 0$ ). Even if the constraint ( $\phi \leq 0$ ) is nonlinear it can be subdivided into more than one linear constraints (linearization).

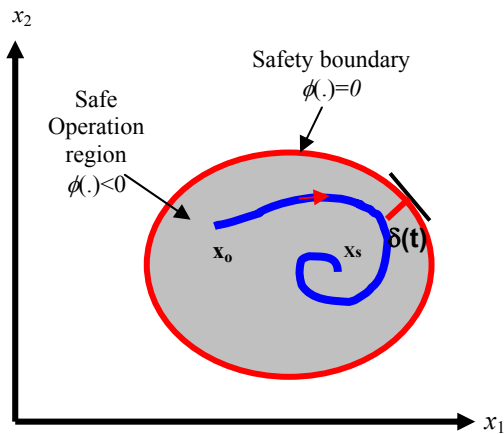


Fig. 3 DSM Definition

*Special case:*

If  $\Phi$  is convex and the boundary constraints are linear in the form of

$$\phi_i(\mathbf{x}) = \mathbf{a}_i \cdot \mathbf{x}_i - c_i \leq 0 : i=1, 2, \dots, q \quad (3)$$

then the distance ( $\delta_i(t)$ ) can be obtained from the following equation

$$\delta_i(t) = \frac{c_i - \mathbf{a}_i \cdot \mathbf{x}(t)}{\|\mathbf{a}_i\|_2} \begin{cases} \geq 0 & \text{iff } \phi_i(\mathbf{x}) \leq 0 \\ \leq 0 & \text{iff } \phi_i(\mathbf{x}) \geq 0 \end{cases} \quad (4)$$

and DSM, is defined as.

$$\delta^*(t) = \min_{1 \leq i \leq q} \delta_i(t) \quad (5)$$

where  $q$  is the number of boundary constraints,  $\mathbf{a}_i$  is a constant row vector,  $c_i$  is a constant value and " $\phi_i(\cdot)=0$ " is a subspace of state vector  $\mathbf{x}_i \in \mathbf{X}$  where  $\mathbf{a}_i \cdot \mathbf{x}_i = c_i$ .

To maintain the system state within a predefined margin of safety, the value of DSM must be considered in controller adapting. The controller parameters should be adapted when the DSM is relatively positive small or negative otherwise the parameters maintain without change.

#### A. Linear Adaptation

The adapted parameters can be defined as a linear function of the DSM and calculated from the following equation:

$$k_i(t + \Delta t) = k_i(t) + \alpha_{1i} \delta^*(t) + \alpha_{2i} \frac{d\delta^*(t)}{dt} \quad i=1, 2, \dots, N \quad (6)$$

where  $\delta^*(k)$  is the DSM at any instance  $k$ ,  $K_i$  controller parameter number  $i$ ,  $N$  total number of controller parameters,  $\alpha_i$  adaptation parameter.

The results of (6) can not insure that the gain changes will move the state in the direction of safe region in all cases, DSM positive. Therefore, replacing  $\delta^*(\cdot)$  in (6) by the term  $\frac{\partial \delta(\cdot)}{\partial k_i}$  can guarantee that and the adaptation equation

$$\text{will be } k_i(t + \Delta t) = k_i(t) + \alpha_{1i} \frac{\delta^*(\cdot)}{\partial k_i} \quad (7)$$

$\frac{\partial \delta(\cdot)}{\partial k_i}$ , in most cases, is nonlinear and not easy to compute. Its computation has not been justified in its work.

#### B. Fuzzy adaptation

A Fuzzy controller based on DSM can be used to calculate the incremental values in the adapted parameters where the relation between controller gains and DSM, in

most cases, is nonlinear and not easy to compute it. In general the input variables to Fuzzy controller are function of DSM, e.g.  $\delta^*$ ,  $d\delta^*/dt$  etc., and the output is the incremental value in the adapted parameters. The adapted parameter is calculated from the following equation

$$\begin{aligned} K_i(k+1) &= K_i(k) + F_{y_i}(k) \\ F_{y_i}(k) &= M(\delta^*(k)) \end{aligned} \quad (8)$$

where  $M$  is the fuzzy function of  $\delta^*(k)$  and  $F_{y_i}$  incremental gain which equal to the fuzzy output number  $i$ . The fuzzy controller parameters (membership functions, number of variable and its limits, ... etc.) are chosen to satisfy the overall system stability.

In each method of adaptation, the adapted parameter value should be bounded in the interval,  $k_i \in [k_{il}, k_{ih}]$ , which satisfy the stability condition.

### C. Predictive controller

The controller requirements can be achieved using a predictive linear quadratic tracking controller [13] with state and input constraints.

If the system model is defined by state space model and the safe region is defined by linear boundaries then the objective function will be:

$$\min_{\mathbf{u}_r} J = \sum_{i=1}^N \|\mathbf{y}_d(k+i) - \mathbf{y}(k+i)\|_{\mathbf{Q}}^2 \quad (9)$$

subject to

$$\begin{aligned} \mathbf{x}(k+1) &= \mathbf{A} \mathbf{x}(k) + \mathbf{B} \mathbf{u}(k) \\ \mathbf{y}(k) &= \mathbf{C} \mathbf{x}(k) \\ \mathbf{d}(k+i) &\geq 0, i=1,2,\dots,N \\ \mathbf{u}_l &\leq \mathbf{u} \leq \mathbf{u}_h \end{aligned}$$

where  $\mathbf{u}_r = [\mathbf{u}(k), \mathbf{u}(k+1), \dots, \mathbf{u}(k+N_u)]^T$ ,  $\mathbf{u} \in \mathcal{R}^m$  the control signal vector,  $\|\mathbf{y}\|_{\mathbf{Q}}^2 = \mathbf{y}^T \mathbf{Q} \mathbf{y}$ ,  $\mathbf{Q}$  the weighting matrix,

$\mathbf{d}(\cdot) = [\delta_1(\cdot), \delta_2(\cdot), \dots, \delta_q(\cdot)]$  is the minimum distance vector between state vector and the boundaries of the safe operation region " $\Phi$ ",  $\mathbf{y}_d(\cdot) \in \mathcal{R}^p$  is the desired output vector,  $\mathbf{y}_d(\cdot) \in \mathcal{R}^p$  is the measured output,  $\mathbf{u}_l$  and  $\mathbf{u}_h$  are the lower and upper control vector limits respectively.

The problem here is an optimization problem with hard constraints [13],[14]. In this case the, the adaptive controller identify the system parameters and the optimization problem is solved each sampling time according to the system identified parameters and the safety constraints.

## IV EXPERIMENTS AND RESULTS

The laboratory plant was configured as described in section II, in the first instance the interconnected valve is closed and the system behaviour as one tank system. Once the left tank reach steady state, the interconnected valve is opened and the overall system behaviour as two tank

system. The control valve 2 simulate the leakage from the two tank (disturbance).

In this case the safety relation, described in section 3, is a function of the tank level rate change ( $dh/dt$ ) and control signal ( $v_i$ ) which simulate the limb movement of the valve.

At steady state the maximum level rate 0.4 l/sec when the valve fully closed  $v_i = -0.5$  (normalized signal 4-20 mA), and at  $v_i = 0.5$  the level rate change -0.4 l/sec.

The safe relation  $\Phi$  is defined by the following equation

$$\begin{aligned} dh/dt + 0.8 v_i - 0.08 &< 0 \\ dh/dt + 0.75 v_i + 0.14 &> 0 \\ -0.4 &< dh/dt < 0.4 \\ -0.5 &< v_i < 0.5 \end{aligned} \quad (10)$$

These equations in (10) are determined according to the behaviour of the system and the safe operation relations between the state variable.

The overall block diagram, of the controlled system using PID controller employing analogical gates for anti-reset wind-up [12] and adapted proportional gain based on the method described in the above section. is shown in Fig. 4. a single analogical-gate namely XOR-gate is used to calculate the integral gain for anti-rest wind-up as follows:

$$K_i = K_{i0} [((u - u_0)/u_0) \oplus (u/u_0)] \quad (11)$$

Where,  $K_i$  and  $K_{i0}$  are the current and the initial integral-gain respectively;  $\oplus$  is XOR-gate symbol and the unsaturated and saturated control commands are  $u_0$  and  $u$  respectively.

The parameters were set nominally to obtain an acceptable response for the two-tank system at  $K_p=4$ ;  $K_D=0.8$  and  $K_i=0.05$ .

In case of real time implementation the interconnected valve was commanded according to the hybrid automaton (Fig. 5) and the desired level of left tank in both cases was 0,3m. After the two-tank system reaches the new steady state the interconnected valve still fully open and the leakage valve was opened on steps (10%, 30%, 50%, and 40%).

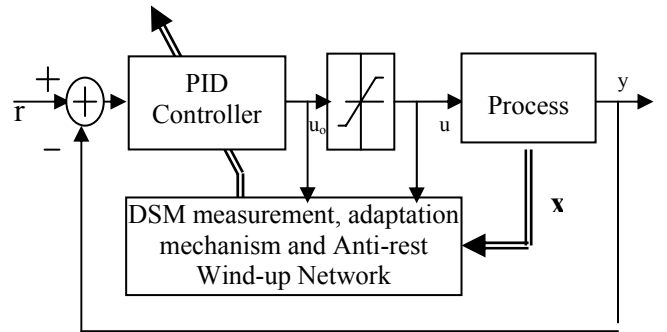


Fig. 4 PID-controller with adapting controller

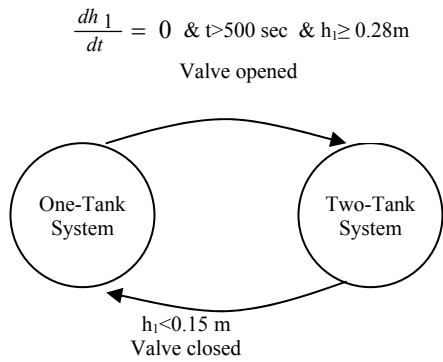


Fig. 5 Hybrid automaton for two-tank system

Fig. 6 shows the real time response, control signal and DSM variation using PID controller without adaptation and the leakage valve open as follow:

0%, 10%, 30%, 50% and 40% open respectively as shown in Fig. 6c.

Note that, the deviation of the output response increases with the leakage valve opening increase.

Fig. 7 shows the real-time response and control signal using linear adapted proportional gain of the PID controller as in (6) with the same leakages as Fig. 6. Where  $\alpha_{i1}=2$  and  $\alpha_{i2}=0$ . Compare the two responses (fixed PID parameters and adapted proportional PID) it is clear that, in case of one-tank or two-tank system, the system response using adapted PID controller based on safety boundary is better than fixed PID either normal or disturbed system. The results insure that considering DSM in adapting controller parameters improves system performance.

Fig. 8 shows real time response using fuzzy adaptation as in (7) for the same disturbance sequence as in Fig. 6. The fuzzy supervisor has one input (deviation from the safe boundary) and one output (incremental proportional gain) with input/output membership function shown in Fig. 9 and Fuzzy allocation matrix shown in Table 3. Normalized input and output signal of fuzzy controller can help in generalize the fuzzy supervisor for more than one parameter adaptation.

The level responses of Fig. 7 and Fig. 8 has not changed with leakage 10% and 30% but it began to change with 50% leakage with small rate and recovered at 40% leakage.

It is clear that, adapting controller parameters, based on DSM, improve the system output performance and can help in safety control of safety critical system.

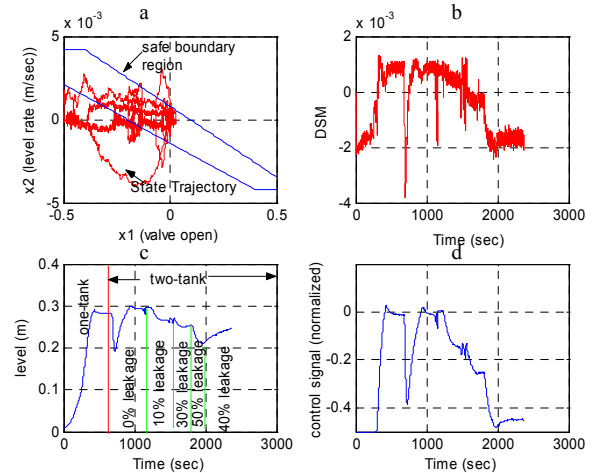


Fig. 6 Level response and DSM using fixed PID parameters

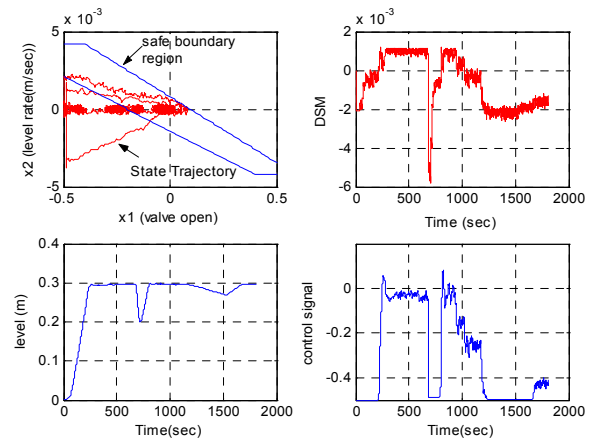


Fig. 7 responses using linear adaptation

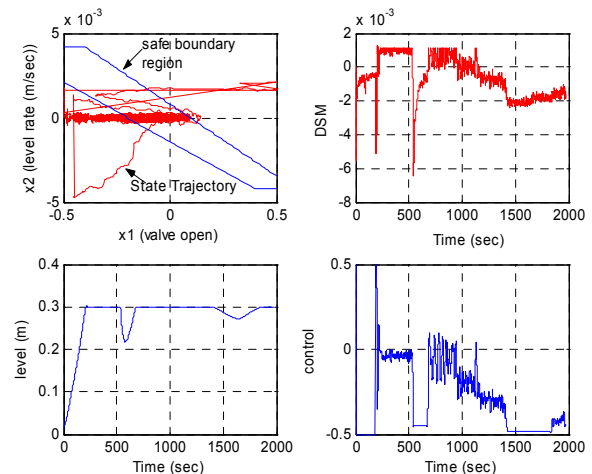


Fig. 8 Responses using fuzzy adaptation

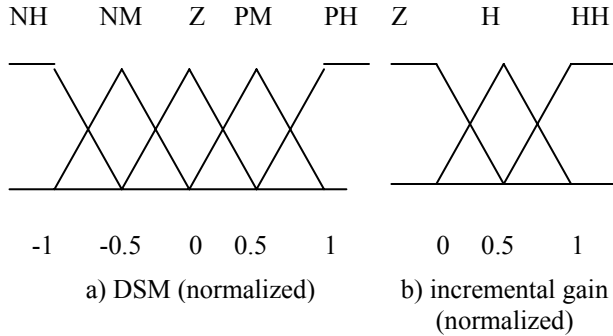


Fig. 9 Membership function of Normalized deviation and incremental gain

Table 3 FAM Of Deviation and incremental gain

$\delta$	NH	NM	Z	PM	PH
$F_{yi}$	HH	H	H	Z	Z

Fig. 10 shows the level response for the two-tank system when the interconnected valve is fully open all the time using predictive controller (11) and the leakage sequence 10% after 500 sec and 30% after 650 sec and 50 after 800 sec. Note that, the level in the left tank is almost around the desired level (30 cm) in normal and leakage case (10% and 30%) and the states lie inside the safe region. while the level has decreased when leakage is 50% but the states still lie inside the safe region. the response of Fig. 10 insure that predictive control with DSM constrain can insure safety operation in normal and faulty case.

### V. CONCLUSION AND FUTURE WORK

In this paper we tried to adapt the controller parameter based on DSM. Adapting the controller parameter based on DSM improves the system response, mainly the system which exposes to non-considerable and non-measurable disturbance, either the system model is well known or there is uncertainly in the system parameters. Adapting PID controller based on DSM has been implemented on an experimental hybrid plant. The main advantage of this adaptation method is that the exact model of the system is less important and we do not need to identify the system parameter each time to reconfigure the controller. Using predictive controller based on DSM give better response than PID one but the algorithm is complex and the computation time is considrably high. Adjusting controller or adapting controller parameters based on DSM are mainly important in FTC system to insure the system safety and recover the system performance in the presense of fault. Using DSM in fault diagnosis and FTC is the next step of the futur work.

### ACKNOWLEDGEMENTS

The authors thanks Dr. Adrian Gambier and Tobias miksich for providing support with QNX and RT Lab at the laboratory, for fruitful discussions and valuable comments.

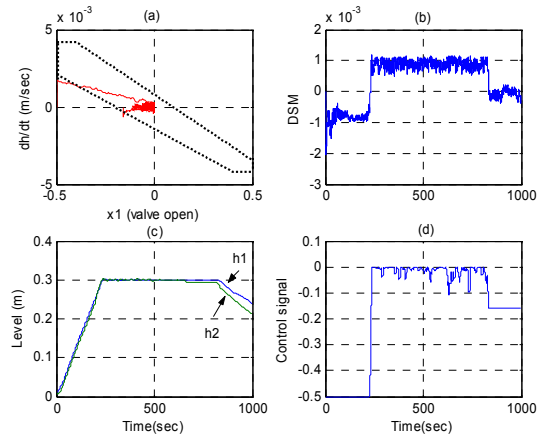


Fig. 10 level response using predictive controller with DSM

### REFERENCES

- [1] E. Badreddin, M. Abdel-Geliel, "Daynamic Safety Margin principle and Application for Safety Critical System", *Procee CCA 2004 IEEE International conference on Control Application*, 2-4 sep. 2004, pp.689-694, Taiwan, 2004.
- [2] Antsaklis P.J., X.D. Koutsoukos and Janan Zaytoon, "on Hybrid control of complex systems: A survey" *European Journal of Automation*, 32, No. 9-10, pp. 1023-1045, 1998.
- [3] Astron, K." *Hybrid Control of inverted pendulums*" In learning , Control and Hybrid Systems, Lecture Notes in Control and Information Sciences, vol. 241, 1999.
- [4] Eker, J. and E. malmborg," Design and implementation of a hybrid control strategy", *IEEE control systems Magazine*, 19, pp. 12-21, 1999.
- [5] K. Dutton ; S. Thompson ; B. Barraclough, "*The art of control engineering*", Addison-Wesley, 1998.
- [6] K Åström, B Wittenmark, "*Adaptive control*", 2nd. ed., Addison-Wesley, 1995.
- [7] M. Abd-El Geliel, M. A. El-Khazendar, "Model Refeence Based Supervisory Fuzzy logic Controller for Process control", *Proc. MIC2003 Conference*, Feb 10-13, 2003, Innsbruck, Austria, pp 262-267.
- [8] M. Abd-El Geliel, M. A. El-Khazendar, "Supervisory Fuzzy logic Controller used for Process loop control in DCS system", *Proc. CCA2003 Conference*, June 23-25, 2003, Istambul, Turkey.
- [9] A. Gambier, t. Miksch, E. Badreddin, „A control Laboratory Plant to Experiment with Hybrid Systems", Proceaccepted to present in the American Control Conference 2003, Denver.
- [10] T. Miksch, "Modeling and Implementation of Experimental Plant", Diploma thesis, Mannheim university, July 2003
- [11] E. Badreddin, "Analogical gates:A Network Logical Gates: A Network Approach to Fuzzy Control with Applications to a Non-holonomic Autonomous Mobile Robot", *International Journal of Intelligent Automation and Soft Computing*, 1997.
- [12] T. Kourti, "Process Analysis and Abnormal situation Detection: From theory to Practice", *IEEE Control System Magazine*, pp. 10-25, October 2002.
- [13] J.A Rossiter, "*Model-Based Predictive Control: Practical Approach*", CRC, 2003.
- [14] F. Borrelli, "Constrained Optimal Control of Linear and Hybrid systems: Lecture Notes in Information Science", Springer, 2003.
- [15] M. Blanke, M. Staroswieki and N. Eva Wu, "Concept and Methods in Fault-tolerant Control", *Tutorial at American Control Conference*, June 2000
- [16] M. Mahmoud, J. Jiang, and Y. Zhang, "*Active Fault Tolerant Control System:Lecture Notes in Control and information Sciences*", Springer, 2003.