STEAM GENERATOR WATER LEVEL CONTROL: A HYBRID SYSTEM APPROACH

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Abstract: The Mixed Logical Dynamical (MLD) formalism is an efficient modeling framework for hybrid systems which allows formulating and solving problems such as moving horizon predictive control and state estimation. This paper presents the application of the combined strategies – state estimation for fault detection and predictive control for water level control – to a steam generator benchmark modeled under a unique MLD form. Indeed, the steam generator is a time varying system for which the sensor failure problem has to be solved. The simulation results show that this unified theoretical scheme allows efficient detection of failures while maintaining the water level within specified limits. *Copyright © 2005 IFAC*

Keywords: Hybrid systems, State estimation, Sensor failures, Fault detection, Predictive control, Steam generators.

1. INTRODUCTION

The problem of water level control of steam generators (SGs) is of crucial importance for EDF (Electricité De France), where nuclear power plants contribute over 70% of the power demand. The physics of such plants requires a smooth and uninterrupted operation, unsatisfactory performance of this controlled system would result in a violation of the safety limits. The main difficulties in designing an effective level control arise from the physics of the plant and measurement reliability. The plant exhibits inverse response behavior due to the so-called “swell and shrink” effects and the flow measurement is less reliable, particularly at low power. Furthermore, sensor redundancy is used to deal with potential sensor failures. The plant is also a time-varying system with dynamics that move slowly as the internal power changes and with unstable open loop response. Finally, both control input and output are constrained.

Several methods based on a non hybrid model of the SG have been applied to control the water level, without considering the sensors failures and with less strict specifications than those considered in this paper, e.g. H_∞ in (Ambos, *et al.*, 1999), PID in (Eborn, *et al.*, 1999).

On the other hand, the Mixed Logical Dynamical (MLD) formalism (Bemporad and Morari, 1999) can describe a large number of important classes of so-called hybrid systems, including both continuous and discrete aspects with dynamics, logic and constraints. Furthermore, it allows formulating and solving problems such as state estimation or control, and receding horizon strategies in that sense provide efficient tools for both aspects. An innovative strategy is thus to combine receding horizon estimation and control within the unique MLD modeling framework, considering the SG benchmark as a hybrid system. This is fully justified by the fault detection feature. A first step in this direction was presented in (Thomas, *et al.*, 2003), where only the problems of state estimation and sensors failure detection were addressed. The purpose of this paper is thus to examine the feasibility of the combination control/estimation on the SG benchmark.

The paper is organized as follows: Section 2 briefly presents the steam generator benchmark and its specifications. The proposed combined estimation and control solution using MLD framework is described in Section 3 in the particular SG case. Section 4 presents the application of this strategy to the steam generator benchmark. Finally, Section 5 presents some conclusions.

2. THE STEAM GENERATOR BENCHMARK

This part briefly summarizes the SG principles and the main features and specifications of the proposed benchmark. A comprehensive description of the benchmark can be found in (Bendotti, *et al.*, 2002).

The main objective in controlling a PWR (Pressurized Water Reactor) is to provide the commanded power while respecting certain physical constraints. The pressurized water in the primary circuit transmits the heat generated by the nuclear reaction to the steam generator (SG). In the SG, water of secondary circuit is converted to steam, which drives a turbo-alternator to generate electricity, Figure 1. The control strategy aims at maintaining the SG water level within permitted limits, even with changes in the steam flow-rate Q_v (connected to changes in the power demand), considered as a disturbance, by acting on the feed-water flow-rate Q_e, considered as the control signal.

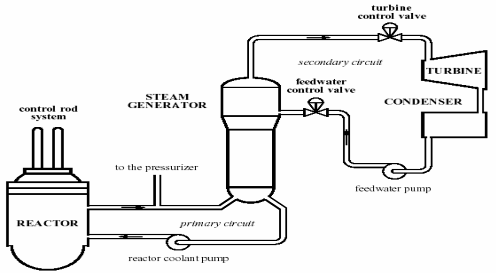

Fig. 1. PWR Description (Bendotti, *et al.*, 2002).

2.1 General description and modeling.

The secondary fluid in the SG turns into a two-phase fluid, steam-water, so that the water level in the SG is not a well defined quantity. Two water level measurements are thus available: the mixture level N_{ge} and the mass of water N_{gl}.

Detailed theoretical models of the SG are too complex for estimation or control purposes. Thus simplified linearized models in state space representation with 5 state variables are derived, with coefficients depending on the operating power and u the control signal applied to the valve actuating the feed flow-rate, $\mathbf{y} = (N_{ge}\ N_{gl}\ Q_v\ Q_e)^{\mathrm{T}}$ the measured outputs, $d = Q_v$ the disturbance. Only two models are considered below, at high power $80\% P_n$ and at low power $10\% P_n$ (P_n is the nominal power), under the generic form (Bendotti, *et al.*, 2002):

$$\begin{aligned} \dot{\mathbf{x}}(t) &= \mathbf{A}\,\mathbf{x}(t) + \mathbf{B}_u\, u(t) + \mathbf{B}_d\, d(t) \\ \mathbf{y}(t) &= \mathbf{C}\,\mathbf{x}(t) + \mathbf{D}\, d(t) \end{aligned} \quad (1)$$

2.2 Sensor redundancy.

To cope with potential sensor failures, sensor redundancy is imposed. In our case, the available measurements are the following:

- Q_{e1} and Q_{e2} sensors, measuring the feed-water flow-rate Q_e, used at high powers ($> 50\% P_n$).
- Q_{v1} and Q_{v2} sensors, measuring the steam flow-rate Q_v, used at high powers ($> 50\% P_n$).
- N_{ge1}, N_{ge2} and N_{ge3} sensors, measuring the narrow range level N_{ge}.
- One sensor measures the wide range level N_{gl}.

In normal operation, each measurement is subject to random independent noise and offset. Furthermore, at low powers ($< 50\% P_n$), where the flow-rate sensors are not reliable, estimates values of Q_e and Q_v ($q_{e-estim}$, $q_{v-estim}$ respectively) are used instead of measured values.

2.3 Benchmark specifications and scenarios.

The transients, following transients are considered:

- T1/T2/T3: A +5% step change on Q_v at power $85\% P_n$ / $10\% P_n$ / $5\% P_n$
- T4: A -3% step change on Q_v at power $10\% P_n$
- T5: A -15%/min ramp corresponding to a 70% change of Q_v starting from 90% P_n
- T6: A -30% step change on Q_v at 60% P_n

The failure scenarios, the considered scenarios are:

- F1: Ideal case, no sensor failure, no bias
- F2: Standard case, no sensor failure, but independent bias applied to all measurements
- F3/F4: A slow/fast drift on one Q_e sensor
- F5/F6: A slow/fast drift on one Q_v sensor
- F7/F8: A slow/fast drift on one N_{ge} sensor
- F9/F10: A slow/fast drift on the N_{gl} sensor

The specifications, the objective is to control the steam generator water level N_{ge} around a constant reference normalized at 0. The specifications are:

- The magnitude of the error on the level N_{ge} for Q_v step response should lie between $\pm 5\,\%$ and die off in less than 100 sec. Then the error should be less than $\pm 0{,}5\,\%$. For transient T5/T6 (involving a loss of reliability in flow-rate measurement), the error should lie between $\pm 10\,\%$ and die off in less than 150 sec. In case of sensors failures, a $\pm 3\,\%$ error is allowed and then should die off as fast as possible, where the settling time should be much smaller for the fast drift than for slow drift, as the latter is more difficult to detect.
- The controller should be in discrete-time with a sampling rate $\geq$ 0.4 sec., including saturation on the control signal $[u_{\min}, u_{\max}] = [4, 120]$.

3. COMBINED SG ESTIMATION & CONTROL USING MLD FRAMEWORK

The MLD model describes systems by linear dynamic equations subject to linear inequalities involving both real and integer variables, see (Bemporad and Morari, 1999). The auxiliary variables are introduced when translating propositional logic into linear inequalities. This formalism can also formulate and solve practical problems such as state estimation or control, and predictive strategies (Camacho and Bordons, 1999) in that sense provide efficient tools. The optimization procedure resulting from the moving horizon predictive control cost function minimization leads to a mixed integer quadratic programming (MIQP) problem. The dual moving horizon estimation problem can also be formulated as a MIQP, based on a MLDF (Mixed Logical Dynamic Fault) model, minimizing a quadratic criterion involving the quantities to be estimated. The estimation horizon extends backwards in time and allows at time t to estimate the quantities of interest at times prior to t, see (Bemporad, *et al.*, 1999). The proposed strategy, developed below in the specific SG case, is a three-step approach which unifies moving horizon fault detection and state estimation, and predictive control under the MLD formalism.

3.1 Sensor fault detection algorithm

Considering the SG, the following assumptions can be made: first, the sensors of a particular output are independent and not influenced by the sensors of the other outputs. Then only one fault (either fast or slow drift) can appear at the same time. This first step aims at designing a sensor fault detection algorithm which will select reliable measurements (i.e. sensors not affected by fault) for further use during the procedure. Each fault on a specified sensor is represented by an auxiliary binary variable $\phi_i \in \mathbf{\Phi}$, $\mathbf{\Phi} = \{0,1\}$, which influences the sensor's output by a quantity requiring the introduction of an additional auxiliary continuous variable z_i, under the form:

$$y_i = y_{si} + z_i \text{ with } z_i = \phi_i\, g \qquad (2)$$

where g is a constant value over the estimation horizon, y_i and y_{si} are respectively the sensor output and the measured variable. Finally, as the fault values g are also unknown, an additional state must be included in the state vector of the MLDF model. As the SG has 8 sensors, each subject to 2 faults, 16 additional binary variables might be added. To reduce the calculation time, only one binary variable for each sensor is used to model the possibility of sensor failure Eq. 2; indeed only fault detection is critical for the control problem, knowing the type of fault is not crucial here. To further reduce the optimization burden, according to the preliminary assumptions, the general problem can be split into p independent MIQPs, each one dedicated to fault detection of the sensors of a measured output y_{si}. It is thus required to solve 4 independent sub-problems for the 4 measured quantities N_{ge}, N_{gl}, Q_v and Q_e. The MLDF formulation will be explained below in the case of the 3 N_{ge} sensors, the methodology being the same for the other measured variables.

Including the disturbance d and the additional state to be estimated g in the initial state vector, the state-space representation of this hybrid system is deduced from Eq. 1, with $\mathbf{x}_f = [g\ d\ \mathbf{x}]^{\mathrm{T}}$ under the form:

$$\dot{\mathbf{x}}_f(t) = \underbrace{\begin{pmatrix} 0 & 0 & 0 \\ 0 & 0 & 0 \\ 0 & \mathbf{B}_d & \mathbf{A} \end{pmatrix}}_{\mathbf{A}_f} \mathbf{x}_f(t) + \underbrace{\begin{pmatrix} 0 \\ 0 \\ \mathbf{B}_u \end{pmatrix}}_{\mathbf{B}_f} u(t)$$
$$y(t) = \underbrace{\begin{pmatrix} 0 & d_{N_{ge}} & \mathbf{C}_{N_{ge}} \\ 0 & d_{N_{ge}} & \mathbf{C}_{N_{ge}} \\ 0 & d_{N_{ge}} & \mathbf{C}_{N_{ge}} \end{pmatrix}}_{\mathbf{C}_f} \mathbf{x}_f(t) + \underbrace{\begin{pmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{pmatrix}}_{\mathbf{D}_f} \underbrace{\begin{pmatrix} z_1 \\ z_2 \\ z_3 \end{pmatrix}}_{\mathbf{z}} \qquad (3)$$

under the following logical relations:

$$\begin{aligned} &\text{if } \phi_i \text{ true then } z_i = g \text{ else } z_i = 0 \quad (m \le g \le M) \\ &\text{NOT}(\phi_1 \text{ OR } \phi_2)\text{OR} \\ &\quad ((\phi_1 \text{ OR NOT } \phi_2)\text{AND NOT } \phi_3)\text{is true} \end{aligned} \qquad (4)$$

The first logical relation is equivalent to:

$$\begin{cases} z_i \le M\,\phi_i \\ z_i \ge m\,\phi_i \end{cases} \quad \begin{cases} z_i \le g - m(1-\phi_i) \\ z_i \ge g - M(1-\phi_i) \end{cases}$$

The second logical relation becomes:

$$\phi_1 + \phi_2 \le 1; \ \ \phi_1 + \phi_3 \le 1; \ \ \phi_2 + \phi_3 \le 1$$

With these transformations, and using Euler's relation for discretization with sampling time T_s, the MLDF formulation for N_{ge} sensors is deduced:

$$\begin{aligned} &\mathbf{x}_f(t+1) = \mathbf{x}_f(t) + T_s\left(\mathbf{A}_f\, \mathbf{x}_f(t) + \mathbf{B}_f\, u(t)\right) \\ &y(t) = \mathbf{C}_f\, \mathbf{x}_f(t) + \mathbf{D}_f\, \mathbf{z}(t) \\ &\mathbf{E}_3\, \mathbf{z}(t) \le \mathbf{E}_4\, \mathbf{x}_f(t) + \mathbf{E}_5 + \mathbf{E}_6\, \boldsymbol{\varphi}(t) \end{aligned} \qquad (5)$$

Noting T the estimation horizon, the objective of the MIQP for sensor fault detection is to find an estimate of the fault vector $\hat{\phi}(t|t)$ and the state:

$$\hat{\mathbf{X}}(t) = \left[\hat{\mathbf{x}}(t-T+1|t), \hat{\mathbf{x}}(t-T+1|t), \cdots, \hat{\mathbf{x}}(t|t)\right] \qquad (6)$$

assuming that the following estimated vectors are known at time $t-1$:

$$\begin{aligned} \hat{\mathbf{Z}}(t-1) &= \left[\hat{\mathbf{z}}(t-T|t-1), \hat{\mathbf{z}}(t-T+1|t-1), \cdots, \hat{\mathbf{z}}(t-1|t-1)\right] \\ \hat{\mathbf{\Phi}}(t-1) &= \left[\hat{\boldsymbol{\varphi}}(t-T|t-1), \hat{\boldsymbol{\varphi}}(t-T+1|t-1), \cdots, \hat{\boldsymbol{\varphi}}(t-1|t-1)\right] \\ \hat{\mathbf{X}}(t-1) &= \left[\hat{\mathbf{x}}(t-T|t-1), \hat{\mathbf{x}}(t-T+1|t-1), \cdots, \hat{\mathbf{x}}(t-1|t-1)\right] \end{aligned}$$

together with the data known at time t:

$$\begin{aligned} \mathbf{U}(t) &= \left[\mathbf{u}(t-T), \mathbf{u}(t-T+1), \cdots, \mathbf{u}(t-1), \mathbf{u}(t)\right] \\ \mathbf{Y}(t) &= \left[\mathbf{y}(t-T), \mathbf{y}(t-T+1), \cdots, \mathbf{y}(t-1), \mathbf{y}(t)\right] \end{aligned}$$

Consider at time t the following estimate evolution:

$$\begin{cases} \hat{\mathbf{x}}_f\left(t-T\middle|t\right)=\hat{\mathbf{x}}_f\left(t-T\middle|t-1\right)+\mathbf{\Delta x}_f(t) \\ \hat{\mathbf{x}}_f\left(t+k+1\middle|t\right)=\hat{\mathbf{x}}_f(t+k|t)+T_s(\mathbf{A}_f\,\hat{\mathbf{x}}_f(t+k|t)+ \\ \qquad +\mathbf{B}_f\,u(t+k)) \\ \hat{\mathbf{y}}\left(t+k\middle|t\right)=\mathbf{C}_f\,\hat{\mathbf{x}}_f(t+k|t)+\mathbf{D}_f\,\hat{\mathbf{z}}(t+k|t) \\ \mathbf{E}_3\,\hat{\mathbf{z}}(t+k|t)\le\mathbf{E}_4\,\hat{\mathbf{x}}_f(t+k|t)+\mathbf{E}_5+\mathbf{E}_6\,\hat{\boldsymbol{\varphi}}(t+k|t) \\ \qquad \text{with} \quad -T\le k\le 0 \end{cases} \tag{7}$$

The quadratic cost function at time t is defined by:

$$\begin{aligned} J(\boldsymbol{\chi}_\mathbf{t}) &= \left\|\mathbf{\Delta x}_f(t)\right\|^2_{\mathbf{Q}_9} + \sum_{k=-T}^{0}\left(\left\|\hat{\boldsymbol{\varphi}}(t+k|t)\right\|^2_{\mathbf{Q}_{10}}\right)+ \\ &+ \sum_{k=-T+1}^{0}\left(\left\|\hat{\mathbf{y}}(t+k|t)-\mathbf{y}(t+k)\right\|^2_{\mathbf{Q}_5}\right)+ \\ &+ \sum_{k=-T+1}^{-1}\left(\left\|\hat{\mathbf{x}}(t+k|t)-\hat{\mathbf{x}}(t+k|t-1)\right\|^2_{\mathbf{Q}_4}\right)+ \\ &+ \sum_{k=-T}^{-1}\left(\begin{aligned}&\left\|\hat{\mathbf{z}}(t+k|t)-\hat{\mathbf{z}}(t+k|t-1)\right\|^2_{\mathbf{Q}_3}+ \\ &\quad+\left\|\hat{\boldsymbol{\varphi}}(t+k|t)-\hat{\boldsymbol{\varphi}}(t+k|t-1)\right\|^2_{\mathbf{Q}_6}\end{aligned}\right) \end{aligned} \tag{8}$$

under the constraints of the model equation Eq. 5. The $\mathbf{Q}_i s$ are symmetric positive semi definite matrices. The optimization vector at time t is:

$$\boldsymbol{\chi}_\mathbf{t}=[\mathbf{\Delta x}(t),\hat{\mathbf{z}}(t-T|t),\cdots,\hat{\mathbf{z}}(t|t),\hat{\boldsymbol{\varphi}}(t-T|t),\cdots,\hat{\boldsymbol{\varphi}}(t|t)] \tag{9}$$

Finally, the measurement estimate is the mean of the sensor values for which $\hat{\varphi}_i(t|t)=0$. The same procedure is repeated for the other sensors.

3.2 State reconstruction

Assuming now that all selected measurements are reliable, the goal of this step is to merge the results of each previous sub-problems and find a global estimate of the state Eq. 6, assuming that $\hat{\mathbf{X}}(t-1)$ is known at time $t-1$, together with $\mathbf{U}(t),\mathbf{Y}(t)$ and the disturbances $\left[d(t-T),\cdots,d(t)\right]$. In this case, the initial model Eq. 1 can be used again as no additional variables will appear. Consider at time t the following estimate evolution:

$$\begin{cases} \hat{\mathbf{x}}\left(t-T\middle|t\right)=\hat{\mathbf{x}}\left(t-T\middle|t-1\right)+\mathbf{\Delta x}(t) \\ \hat{\mathbf{x}}\left(t+k+1\middle|t\right)=\hat{\mathbf{x}}(t+k|t)+T_s(\mathbf{A}\,\hat{\mathbf{x}}(t+k|t)+ \\ \qquad +\mathbf{B}_u\,u(t+k)+\mathbf{B}_d\,d(t+k)) \\ \hat{\mathbf{y}}\left(t+k\middle|t\right)=\mathbf{C}\,\hat{\mathbf{x}}(t+k|t)+\mathbf{D}\,d(t+k) \\ \qquad \text{with} \quad -T\le k\le 0 \end{cases} \tag{10}$$

The quadratic cost function at time t giving through MIQP the state estimate $\hat{\mathbf{X}}(t)$ is defined by:

$$\begin{aligned} J(\mathbf{\Delta x}(t)) &= \sum_{k=-T+1}^{-1}\left(\left\|\hat{\mathbf{x}}(t+k|t)-\hat{\mathbf{x}}(t+k|t-1)\right\|^2_{\mathbf{Q}_4}\right)+ \\ &+\left\|\mathbf{\Delta x}_f(t)\right\|^2_{\mathbf{Q}_9}+\sum_{k=-T+1}^{0}\left(\left\|\hat{\mathbf{y}}(t+k|t)-\mathbf{y}(t+k)\right\|^2_{\mathbf{Q}_5}\right) \end{aligned} \tag{11}$$

3.3 MPC control algorithm

Based on the model Eq. 1, an integral term is added on the N_{ge} variable in order to cancel steady state error, so that the model considered for control is:

$$\begin{cases} \hat{x}_{\text{int}}\left(t+k+1\middle|t\right)=\hat{x}_{\text{int}}\left(t+k\middle|t\right)+T_s\,\mathbf{C}_{N_{ge}}\,\hat{\mathbf{x}}(t+k|t) \\ \hat{\mathbf{x}}\left(t+k+1\middle|t\right)=\hat{\mathbf{x}}(t+k|t)+T_s(\mathbf{A}\,\hat{\mathbf{x}}(t+k|t)+ \\ \qquad +\mathbf{B}_u\,u(t+k)+\mathbf{B}_d\,d(t+k)) \\ \hat{\mathbf{y}}\left(t+k\middle|t\right)=\mathbf{C}\,\hat{\mathbf{x}}(t+k|t)+\mathbf{D}_d\,d(t+k) \\ \qquad \text{with} \quad 0\le k\le T_c-1 \end{cases} \tag{12}$$

The following model predictive control problem is finally considered. Let t be the current time, $\hat{\mathbf{x}}(t)$ the current estimated state, $(\mathbf{x}_e,\mathbf{u}_e)$ an equilibrium pair or a reference trajectory value, and T_c the prediction horizon, find the control sequence $\mathbf{u}_t^{t+T_c-1}=\left(\mathbf{u}(t)\ \cdots\ \mathbf{u}(t+T_c-1)\right)$ moving the state from $\hat{\mathbf{x}}(t)$ to $\mathbf{x}_e$ and minimizing the criterion:

$$\begin{aligned} \min_{\mathbf{u}_t^{t+T_c-1}} J &= \sum_{k=0}^{T_c-1}\left\|\mathbf{u}(t+k)-u_e\right\|^2_{\mathbf{Q}_1}+\left\|\hat{x}_{\text{int}}(t+k|t)\right\|^2_{\mathbf{Q}_{\text{int}}} \\ &+\left\|\hat{\mathbf{x}}(t+k|t)-\mathbf{x}_e\right\|^2_{\mathbf{Q}_4}+\left\|\hat{\mathbf{y}}(t+k|t)-\mathbf{y}_e\right\|^2_{\mathbf{Q}_5} \end{aligned} \tag{13}$$

subject to Eq. 12, including constraints on the control signal as mentioned in Section 2.3, and on the control increments as stated below. The optimisation procedure of Eq. 13 leads again to a MIQP problem providing the control $u(t)$ applied to the process.

4. APPLICATION

In this section, an application of the previous strategy to the water level control of the SG is presented. A Simulink program is developed, including the plant model as a S-function, the estimation part (M-function) that takes the data from the SG sensors, and the control program (M function) fed with the estimation part results.

4.1 Implementation issues of the control strategy

1- A prediction horizon equal to 5 is used with a sampling time $T_s=0.5\,\text{sec}$.

2- Constraints on the control update are added:

$$\Delta u(k)=\left|u(k)-u(k-1)\right|\le 5$$

3- Successive iterations show that the best configuration switching from the high to the low power SG model corresponds to 25% power level.

4- For the considered scenarios, and after successive iterations, three controllers are designed with the following weighting factors sets:

- High power controller:

  $\mathbf{Q}_1=9\,\mathbf{I}$; $\mathbf{Q}_2=20\,\mathbf{I}$; $\mathbf{Q}_5=560\,\mathbf{I}$; $Q_{\text{int}}=1$

- Low power controllers (two controllers are necessary as the system dynamic changes too much with the demanded power in this range):

i. For power between 12 and 25 % P_n :

$\mathbf{Q}_1 = 0.15\ \mathbf{I}$; $\mathbf{Q}_2 = 2.5\ \mathbf{I}$; $\mathbf{Q}_5 = 18\ \mathbf{I}$; $Q_{\text{int}} = 0.03$

ii. For power less than 12 % P_n :

$\mathbf{Q}_1 = 0.15\ \mathbf{I}$; $\mathbf{Q}_2 = 2.5\ \mathbf{I}$; $\mathbf{Q}_5 = 18\ \mathbf{I}$; $Q_{\text{int}} = 0.012$

5- Regarding the transient T5, a linear transition from the Q_v, Q_e sensors to the estimated values is realized to avoid the jump from measured to estimated values, Figure 3.

- For Q_v, transition from sensors q_{v1}, q_{v2} at 55% P_n towards q_{v_estim} at 35 % P_n
- For Q_e, transition from sensors q_{e1}, q_{e2} at 54% P_n towards q_{e_estim} at 42 % P_n

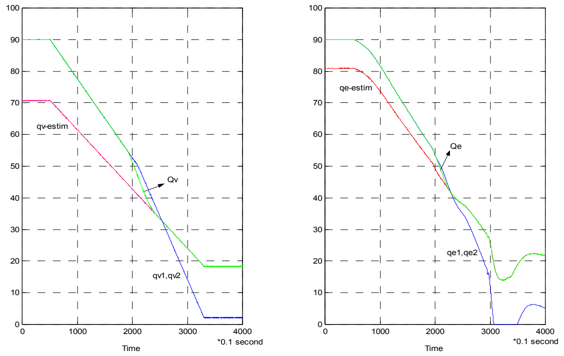

Fig. 2. Linear transition of flow rates Q_v, Q_e sensors.

4.2 *Implementation issues of the estimation strategy*

1- The 4 sub-problems for the 4 measured quantities: N_{ge}, N_{gl}, Q_v and Q_e were achieved with the estimation horizons $T = 1, 6, 3, 1$ respectively.

2- The following diagonal weighting matrices (for all the sub-problems) are chosen:

$$\mathbf{Q}_3(\mathbf{z}) = 3000\mathbf{I}; \mathbf{Q}_4(\mathbf{x}) = 30\mathbf{I}; \mathbf{Q}_6(\Delta\boldsymbol{\varphi}) = 500\mathbf{I};$$

$$\mathbf{Q}_5(\mathbf{y}) = 1000000\mathbf{I}; \mathbf{Q}_{10}(\boldsymbol{\varphi}) = 7000\ \mathbf{I}; \mathbf{Q}_9(\Delta\mathbf{x}) = 0.1\mathbf{I}$$

3- A sampling time equal to 0.1 second is used.

4– At low power, no state estimation on Q_v and Q_e is realized, taking as an alternative the $q_{v-estim}$ and $q_{e-estim}$ values.

4.3 *Simulation results*

In the following, some simulation results with a simulation sampling time of 0.1 s. are presented. The scenario T1-F4 is first considered; Figure 3a shows that the estimation strategy succeeds in detecting the fault occurrence without any delay. Only sensor outputs affected by fault are shown in these figures. Figure 3b presents the results of the SG water level control where all the specifications are satisfied.

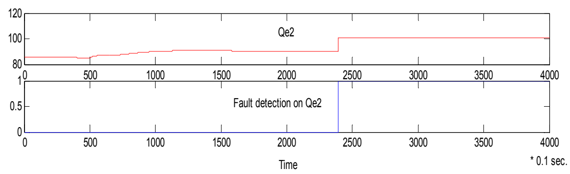

Fig. 3a. Results of fault detection on Q_e, (T1-F4).

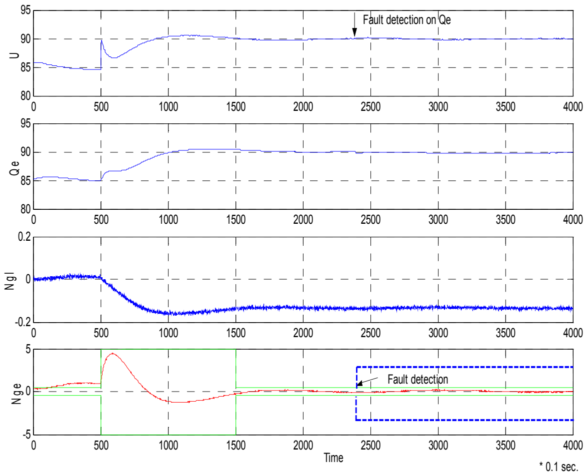

Fig. 3b. Control results, with scenario T1-F4.

In the case of scenario T2-F8, Figure 4a presents the results of fault detection where also the hybrid strategy detects the fault without any delay. All control specifications are satisfied, Figure 4b.

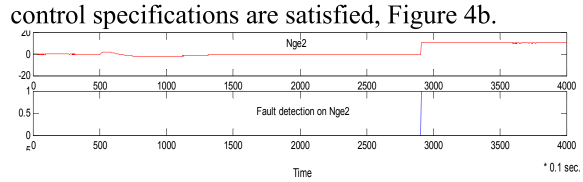

Fig. 4a. Results of fault detection on N_{ge}, (T2-F8).

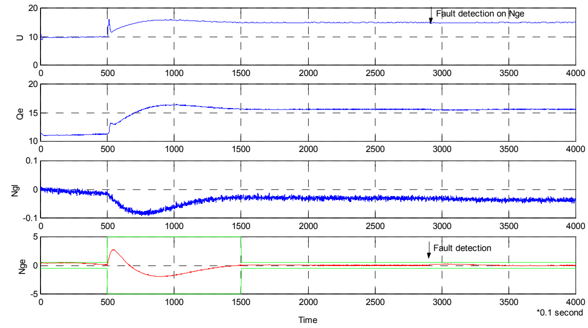

Fig. 4b. Control results, with scenario T2-F8.

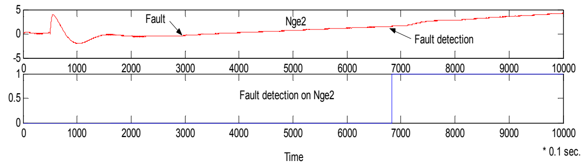

Fig. 5a. Results of fault detection on N_{ge}, (T3-F7).

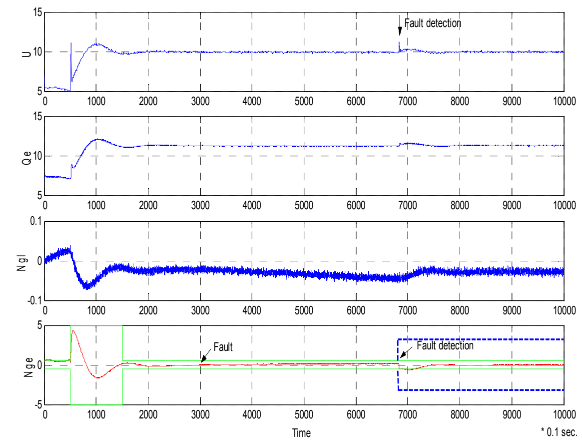

Fig. 5b. Control results, with scenario T3-F7.

In the case of scenario T3-F7, Figure 5a presents the results of fault detection where the hybrid strategy detects the fault with acceptable delay. Again all control specifications are satisfied, Figure 5b.

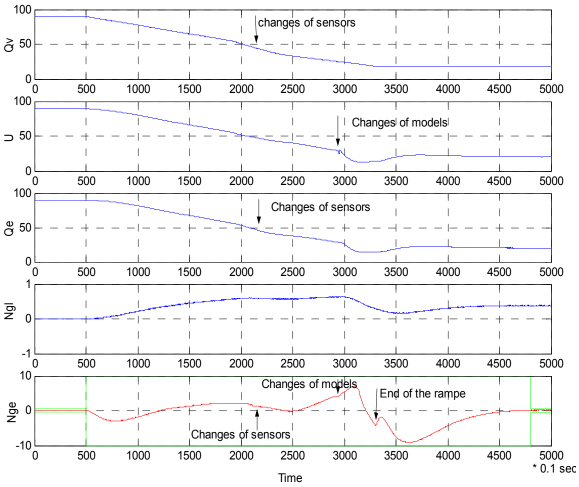

Fig. 6. Control results, with scenario T5-F2.

Figure 6 presents the results of standard case where model and measured-estimated values changes take place (T5-F2). All the specifications are satisfied. However, some works remain in order to consider evolution of models and changes from measured to estimated values as a result of an optimization process taking into account additional binary variables. Finally, Figure 7 presents collective results of differrent transients and fault scenarios.

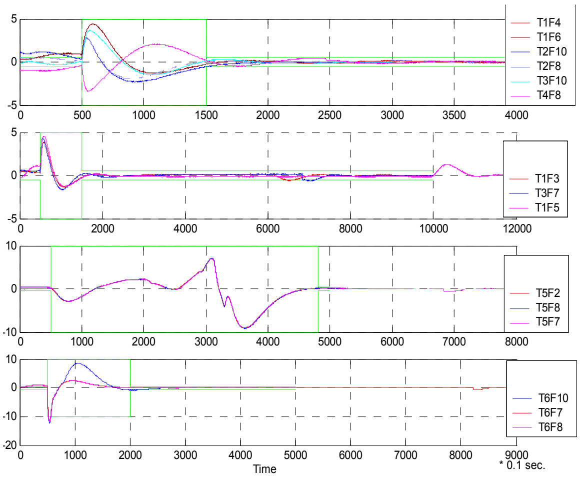

Fig. 7. N_{ge} level control, for different transients.

Results presented here and other tests not shown due to space limitation provide the following remarks. The estimation strategy succeeds in detecting the fast drift fault without any delay and the slow drift fault with acceptable delay; this delay depends on the fault value, the weighting factors and on the estimation horizon (Thomas, *et al.*, 2003). The fault detection on N_{ge} is relatively simple as there are 3 sensors, only one of them could be subject to any fault. Also the fault detection on Q_e is simple, as the Q_e value directly depends on the control signal. The detection of faults on Q_v is more difficult (in the case of slow drift), as it is considered in the model as an input disturbance. The fault on N_{gl} is the most difficult to detect (for the slow drift fault) as there is only one sensor available. The last two cases can be improved increasing the estimation horizon.

The control strategy succeeds in satisfying all the SG specifications, except in the two following cases:

1- For scenario T6 the error is little more than 10% (and less than 12%), that is actually not because of the fault effect, but because of the big step value on Q_v , about 35%.

2- In the case of slow drift on N_{gl} , the value of N_{ge} strongly depends on the N_{gl} value, which leads the error on N_{ge} to a big value before detecting the fault occurrence. To avoid this problem a longer estimation horizon for N_{gl} is required to detect the fault earlier.

5. CONCLUSION

This paper presents a strategy applied to the water level control of a steam generator, combining state estimation for fault detection and predictive control within a unique framework of a hybrid system under the MLD form. This strategy enables to ensure almost all fault detection and control specifications. Due to the particular structure of the studied system, improvements in the problem formulation make real time implementation possible. Future work may consider including additional binary variables taking into account in the optimization phase commutations of models and measurement features.

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