# A COMBINED APPROACH TO FAULT DIAGNOSIS IN DYNAMIC SYSTEMS

## *Application to the Three-Tank Benchmark*

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Abstract: This paper presents a combined approach to fault diagnosis in discrete-time dynamic systems. The approach integrates classical and soft computing techniques. The typical methods based on signal models, and process models for residual generation are considered: parity equations, observers and parameter estimation. The role of integration of classical and intelligent techniques is enhanced. The performance of the proposed approach is analysed with application to a typical nonlinear feed-water system – the three-tank benchmark. The three typical fault scenarios (actuator and component faults) defined in the benchmark problem are tackle in this work.

## 1 INTRODUCTION

Modern supervision and control systems are becoming more and more sophisticated. The issues of reliability, operating safety, availability, cost efficiency, and environment protection are of great importance. For safety-critical systems, the consequences of faults can be extremely serious in terms of human fatalities, environment impact or economic loss. There is a growing need for on-line supervision and fault diagnosis (FDI) to increase the reliability of such safety-critical systems (Chen and Patton, 1999). For systems that are not safety-critical, on-line FDI techniques can be use to improve reliability, plant efficiency, availability, and maintainability.

Since the beginning of the 1970's, research in fault diagnosis has been gaining increasing consideration world-wide in both theoretical and application areas (Chen and Patton, 1999; Frank, *et. al.*, 1999; Gertler, 1998; Isermann, 1997; Patton, *et. al.*, 2000). This development was (and still is) mainly stimulated by the trend of automation towards more complexity and the growing demand for higher security and availability of supervision and control systems. The great progress of computer technology made feasible the use of powerful techniques of modern and intelligent control theory applied to the FDI problems, like mathematical modelling, state estimation and parameter identification.

The main purpose of fault diagnosis is the determination of kind, size, location and time occurrence of a fault (Isermann, 1997). Many approaches to FDI in the time as well in the frequency domain have been proposed (Chen and Patton, 1999; Frank, *et. al.*, 1999; Gertler, 1998; Isermann, 1997; Patton, *et. al.*, 2000). From the multiple model-based methods in the literature, the three main groups are parity equations, observers, and parameter estimation. Fault detection based on signal processing and on signal models is also possible (Isermann, 1997).

A "fault" is an unexpected change of a system function, although it may not represent physical failure or breakdown (Chen and Patton, 1999). Another definition is (Isermann, 1997): a "fault" is a non-permitted deviation of a characteristic property that leads to the inability to fulfil the intended purpose.



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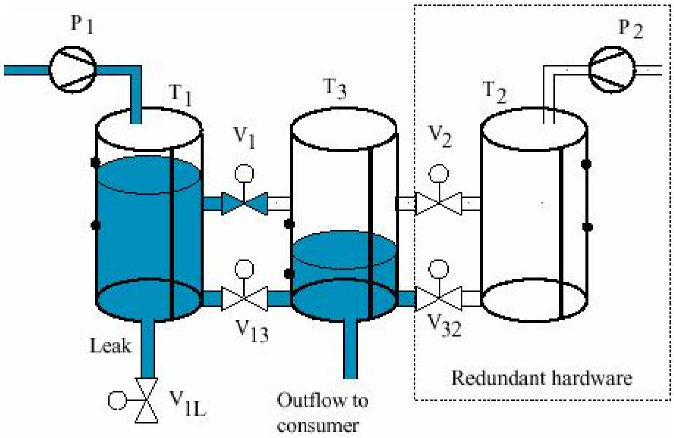


Figure 1: The three-tank benchmark.

Modern fault diagnosis systems are model-based, instead of the traditional approach based on "hardware (or physical/parallel) redundancy. Two kinds of models can be used to perform the FDI task (Chen and Patton, 1999; Frank, *et. al.*, 1999; Gertler, 1998; Isermann, 1997; Patton, *et. al.*, 2000): quantitative (analytical) models, or qualitative models (knowledge-based models: fuzzy models, neural networks, etc). Model-based fault diagnosis is define as the determination of faults of a system from the comparison of available system measurements with a priori information represented by the system's mathematical model, through generation of residual signals and their analysis. A residual is a fault indicator or an accentuating signal that reflects the faulty situation of the monitored system (Chen and Patton, 1999).

Some process plants are complex systems, like nuclear reactors, chemical plants, aircrafts, power plants, feed-water plants, etc. For that cases, an efficient FDI approach must combine (integrate) different FDI methods: parity equations, observers, and parameter estimation. These methods can be implemented using classical or intelligent soft computing techniques. The three-tank benchmark used in our work (Figure 1), developed during the COSY (control of complex systems) programme of the European Science Foundation, is a typical hybrid complex system (Heiming and Lunze, 1999). The main reasons are: a) each water tank is a nonlinear system; b) is a hybrid system in the sense that has continuous and discrete sensors; c) has eight different operating modes; d) the models build to represent the system behaviour usually have a significant uncertainty associated.

The main contribution of this paper is the integrated approach proposed to deal with nonlinear FDI problems in hybrid nonlinear dynamic systems, where nonlinear neural observers play an important role. Section 2 describes, briefly, the three-tank benchmark. Section 3 details the proposed combined approach for FDI, and the application to the benchmark. The simulation results are in section 4. The final section presents the conclusions and the future work.

## 2 THE THREE-TANK BENCHMARK

The benchmark problem concerns the three coupled-tanks depicted in Figure 1 (Heiming and Lunze, 1999). The aim is to provide a continuous water flow $Q_N$ to a consumer by maintaining a desired level in the central tank $T_3$. Pipes, which can be controlled by several valves, connect the water tanks. All valves can only be completely opened or completely closed. Water can be let into the left and right tank using two identical pumps (P1 and P2). Measurements available from the process are the continuous water levels $h_i$ in each tank, and two discrete levels $h_d$ from two proximity switches attached to the central tank ($T_3$). For the middle tank $T_3$, the qualitative values are: *low = [0..9] cm, medium = [9..11] cm, and high = [11..60] cm.*

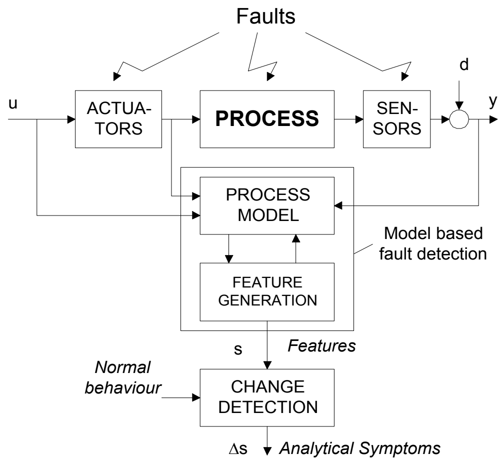


Figure 2: General model-based scheme for fault detection.

In the fault-free situation, only the left tank $T_1$ and the middle tank $T_3$ are used. A continuous PI-controller or other type of controller can be used to control the level around 0.5 m at tank $T_1$. A switching (on-off) controller opens and closes valve $V_1$ thus maintaining the level around 0.1 m at tank $T_3$; the water level in this middle supply-tank has therefore to be maintained at a level $h_3 = medium$. All other valves are closed, and the right tank $T_2$ is empty. The three standard fault scenarios considered are in this work: a) *fault F1*, valve V1 is closed and blocked; b) *fault F2*, valve V1 is open and blocked; c) *fault F3*, valve V1L is open (simulating a leak in tank T1).

The 3-tank benchmark was developed mainly for FDI and for controller reconfiguration tasks. The main problem is to find a new control strategy if a fault in the technical plant has occurred. In this work, only the fault diagnosis problem is considered. The fault-tolerant control problem will be analysed in a future work.

# 3 THE COMBINED FAULT DIAGNOSIS APPROACH

## 3.1 The General Model-Based Scheme for FDI

A general scheme of process-model-based fault detection is depicted in Figure 2 (Isermann, 1997). Based on measured input signals $u$ and output signals $y$, the detection methods generate features $s$ (residuals $r$, parameter estimates $\hat{\theta}$ or state estimates $\hat{x}$). By comparison with the normal features, changes of features are detected, leading to analytical symptoms $\Delta s$.

After fault detection, the fault isolation task must be performed and consists in symptom evaluation and decision-making, in order to decide the location of the fault – a sensor fault, an actuator fault or a component fault, and the time of occurrence.

## 3.2 The Combined FDI Approach

The combined approach proposed in this paper, to solve fault diagnosis (FDI) problems in nonlinear dynamic systems, is based on a combination of different FDI approaches detailed in the next sub-sections.

The neural observer proposed plays an important role in the combined approach, since it's able to works simultaneously as a state and outputs observer.

First one must define the type of faults (additive or multiplicative, and their location - on the sensors, on the actuators or on the process components) that are to be detected, and then use these elements as a guideline to build the process models and signal models for FDI.

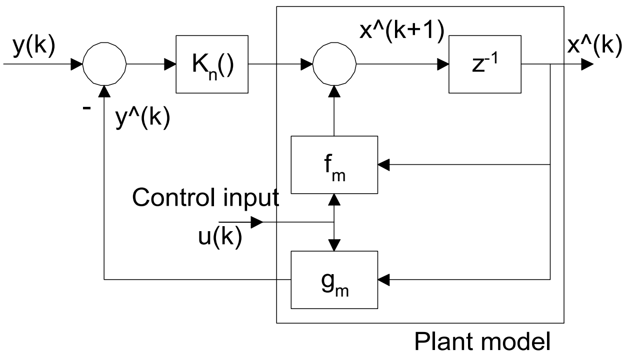


Figure 3: Structure of a nonlinear observer.

## 3.3 FDI based on Signal Processing and Signal Models

In practice, the most frequently used diagnosis method is to monitor the value (or trend) of a particular signal, and taking action when the signal reached a given threshold (Chen and Patton, 1999). This method of limit checking, whilst simple to implement, has at least two main drawbacks: a) the possibility of false alarms in the event of noise, and the change of operating point; b) a single fault could cause many signals to exceed their limits and appear as multiple faults.

In our work, the nominal qualitative level in tank T3, controlled by a switching (on-off) controller, must be *medium*. The discrete sensors (in conjunction to other residuals) can be used to detect the occurrence of a fault (F1, or F2) on the system. A signal $h3d(k)$ was defined based on the discrete sensors information:

$$h3d(k) = \begin{cases} 1 \Leftarrow h_3 = high \\ 0 \Leftarrow h_3 = medium \\ -1 \Leftarrow h_3 = low \end{cases} \quad (1)$$

More advanced methods based on signal models, like the determination of autocorrelation functions, the Fast Fourier Transform (FFT), etc, can also be used to perform fault diagnosis (Isermann, 1997).

## 3.4 FDI via Parity Equations

In the early development of fault diagnosis, the parity equation approach was applied to static or parallel redundancy schemes, which may be obtained directly from measurements or from analytical relations. There are typically two cases for arranging hardware redundancy, one is the use of sensors having identical or similar functions to measure the same variable, another is the use of dissimilar sensors to measure different variables but with their outputs being relative to each other. The basic idea of the parity equation method is to provide a proper check of the parity (consistency) of the measurements of the monitored system (Chen and Patton, 1999; Gertler, 1998).

This type of approach is not used in this work, but it can be used to diagnose, for example, additive faults on sensors.

## 3.5 FDI based on Observers

The basic idea behind the observer or filter-based classical approaches is to estimate the outputs of the system from the measurements by using either Luenberger observer(s) in a deterministic setting, or Kalman filter(s) in a stochastic setting (Friedland, 1996; Chen and Patton, 1999). For a nonlinear system, the structure of the observer is not nearly obvious as it is for a linear system (Friedland, 1996). Let's assume a nonlinear stochastic dynamic model for a nonlinear plant:

$$\begin{cases} x(k+1) = f_m(x(k), u(k), Q(k)) \\ y(k) = g_m(x(k), u(k), R(k)) \end{cases} \quad (2)$$

where $x(k) \in R^n$ is the state, $u(k) \in R^r$ is the input vector, $y(k) \in R^m$ is the system output vector, and $f_m(...)$ and $g_m(...)$ are nonlinear functions. The matrices $Q(k)$ and $R(k)$ are the process and measurement noises. Assuming known the noise characteristics, an Extended Kalman Filter (EKF) can be used as a nonlinear observer; in practice the spectral densities matrices $Q(k)$ and $R(k)$ are hardly ever known to be better than an order of magnitude. For a deterministic system, assuming $Q(k)=0$ and $R(k)=0$, a general nonlinear observer in discrete-time is depicted in Figure 3, and can be expressed by:

$$\begin{cases} \hat{x}(k+1) = f_m(\hat{x}(k),u(k)) + \mathrm{K}_n r(k) \\ r(k) = y(k) - \hat{y}(k) = y(k) - g_m(\hat{y}(k),u(k)) \\ e(k) = x(k) - \hat{x}(k) \end{cases} \quad (3)$$

In (3), $\hat{x}(k) \in R^n$ is the observed state, $u(k) \in R^r$ is the input vector, $y(k) \in R^m$ is the system output vector, and $f_m(...)$ and $g_m(...)$ are nonlinear functions. The residual is expressed by $r(k)$, and $e(k)$ is the estimation error. By proper choice of the nonlinear function $K_n(...)$, the error equation can be made asymptotically stable.

In our work, observers based on neural networks were used to estimate the system outputs (Palma, *et. al.*, 2003; Palma, *et. al.*, 2004). The nonlinear neural observer used in this work obeys the model (3), and has a recurrent dynamic structure. For our case, the state variables are the measured output variables of the system (the levels at the two coupled tanks $T_1$ and $T_3$): $x(k) = \begin{bmatrix} h_1(k) \\ h_3(k) \end{bmatrix}$. In that case the FDI residual $r1oe(k)$ is equal to the residual of the neural observer, $r_1(k) = h_1(k) - \hat{h}_1(k)$. For the state variable $x_1(k) = h_1(k)$, the neural observer is expressed by:

$$\hat{h}_1(k+1) = NN_{\{a,b,c\}}(W, \hat{h}_1(k), q_1(k-1)) + \\ + K_{n1} r_1(k) \quad (4)$$

In a similar way, for tank T3, the residual $r3oe(k)$ is equal to the residual of the neural observer, $r_3(k) = h_3(k) - \hat{h}_3(k)$. For the state variable $x_3(k) = h_3(k)$, the neural observer is expressed by:

$$\hat{h}_3(k+1) = NN_{\{a,b,c\}}(W, \hat{h}_3(k), h_1(k), V_1(k)) + \\ + K_{n3} r_3(k) \quad (5)$$

In equations (4) and (5), $NN_{\{a,b,c\}}(...)$ represents a multi-layer perceptron feed-forward neural network (MLP-FF-NN) with weight matrix $W$ (Hagan, 1995; Palma, *et. al.*, 2003). The structure $\{a=2, b=4, c=1\}$ defines the number of neurons in each layer, respectively, the input layer, the hidden layer, and the output layer. The train of the MLP-FF-NN neural network was done off-line in a set-point range varying between 0.35 and 0.5 m, using the Levenberg-Marquardt backpropagation optimization algorithm. The continuous levels in each tank are $h_1(k)$, and $h_3(k)$. The flow from pump $P1$ is $q_1(k)$, and the switch control signal $V_1(k)$ acts on the switching controller. The nonlinear function $K_{n1}(k)$ is a design parameter that adjusts the observer dynamics and guarantees the stability. In the experiments, this nonlinear gain functions were defined as $K_{ni}(k) = K_i |r_i(k)|$, for constants $K_1 = 0.2$ and $K_3 = 0.5$. These values were tested in simulations, in order to obtain a stable and slow dynamics.

## 3.6 FDI via Parameter Estimation

Model-based FDI can also be achieved by the use of system identification techniques. In most practical cases, the process parameters are not known at all, or are not known exactly enough. Then they can be determined with parameter estimation methods by measuring input and output signals if the basic structure of the model is known (Isermann, 1997). This approach is based on the assumption that the faults are reflected in the physical system parameters such as resistance, capacitance, viscosity, friction, etc. The basic idea of the detection method is that the parameters of the actual process are repeatedly estimated on-line using well known parameter estimation methods (RLS, Kalman filter, etc), and the results are compared with the parameters of the reference model obtained under the faulty-free condition. Any substantial discrepancy is due to a fault. This approach normally uses the input-output mathematical model of a system in the following form (Chen and Patton, 1999):

$$y(k) = f(P, u(k)) \quad (6)$$

where, $P$ is the model coefficient vector which is directly related to physical parameters of the system. The function $f(.,.)$ can be linear or nonlinear. To generate residuals using this approach, an on-line parameter identification algorithm should be used. The residual can be defined in either of the following ways (Chen and Patton, 1999):

$$r(k) = \hat{P}(k) - P(k_0) \tag{7}$$

$$r(k) = y(k) - f(\hat{P}(k-1), u(k)) \tag{8}$$

In this work, an adaptive residual generator based on an ARX model was used. A Kalman filter was used as a parameter estimator for identification of the parameters of the ARX model (Soderstrom and Stoica, 1989). It was assumed that the dynamics of the tank $T_1$ is modelled, in steady-state, by an autoregressive $ARX(na = 2, nb = 1, nk = d = 2)$ model, assuming $e(k)$ is a white Gaussian noise (Soderstrom and Stoica, 1989):

$$\begin{aligned} &A(z^{-1})y(k) = z^{-d}B(z^{-1})u(k) + e(k) \\ &A(z^{-1}) = 1 + a_1 z^{-1} + a_2 z^{-2}; B(z^{-1}) = b_2 = b_0 \end{aligned} \tag{9}$$

A residual was constructed based on (7), for the static gain of the model (9), as defined by (Palma, *et. al.*, 2004):

$$\begin{aligned} &rg1(k) = sg1(k) - sg1(kb) \Leftarrow k > kb \\ &rg1(k) = sg1(k) - \mu(sg1(k - L + 1 : k)) \Leftarrow \ldots \\ &\qquad ka \le k \le kb \end{aligned} \tag{10}$$

## 3.7 Thresholds and Symptoms Values

The thresholds ($ThrH_r$ – high, and $ThrL_r$ – low) for each residual were computed according to a $3\sigma_r$ (standard deviation) limit around the mean value $\mu_r$; these statistical values were computed in a nominal region (Palma, *et. al.*, 2003; Palma, *et. al.*, 2004).

Each residual signal was converted to the range {-1;0;+1}. The value "+1" means that the residual exceeds the upper threshold ($r_x(k) > ThrH_r$), "-1" means that $r_x(k) < ThrL_r$, and "0" means the residual is bounded ($ThrL_r < r_x(k) < ThrH_r$).

## 3.8 The Fault Diagnosis Structure

Based on the 4 symptoms referred, the following fault isolation structure was build according to simulation tests:

*Table 1: Fault isolation structure.*

| | | *Faults* | |
|---|---|---|---|
| | *F1* | *F2* | *F3* |
| *Symptoms* | | | |
| *rg1(k)* | +1 | -1 | -1 |
| *r1oe(k)* | 0 | 0 | -1 |
| *r3oe(k)* | +1 | 0 | 0 |
| *h3d(k)* | -1 (low) | +1 (high) | 0 (med) |

## 3.9 The Adaptive Polynomial Linear Quadratic (LQ) Controller

Liquid level systems, like the one used in this work, are typical nonlinear systems. To control the level at tank $T_1$ an optimal linear quadratic (LQ) controller, based on a polynomial approach, was designed and implemented (Lewis, 1996). For the ARX(2,1,2) model (9), the obtained control law is defined by (11).

The control action $u(k)$ is computed each time instant based on the on-line identified parameters of the ARX model: $a_1(k), a_2(k), b_2(k) = b_0(k)$.

The Kalman filter was used as a parameter estimator. The reference signal is denoted $w(k)$. The scalar $r_0$ is a design parameter used to tune the closed-loop performance.

$$\begin{aligned} u(k) = -\frac{1}{b_2 + \frac{r_0^2}{b_2}}&(-(a_1 b_2 + \frac{r_0^2}{b_2})u(k-1) + \\ &+ (a_1^2 - a_2)y(k) + (a_1 a_2)y(k-1) - w(k)) \end{aligned} \tag{11}$$

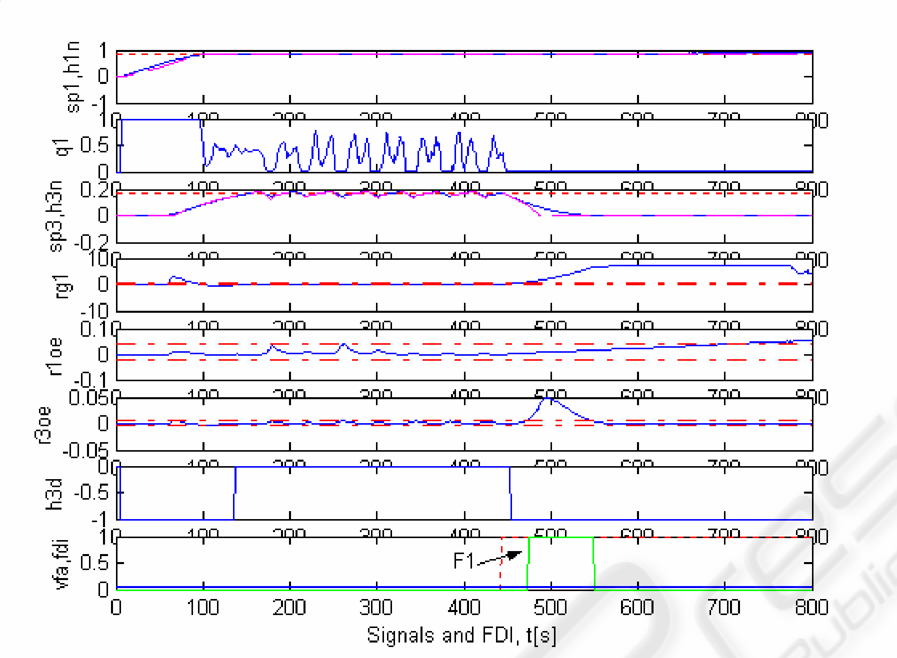


Figure 4: Signals for fault F1.

# 4 SIMULATION RESULTS

## 4.1 Operating Conditions

The simulations were done in a Matlab/Simulink® programming environment. The Simulink model of the three-tank benchmark runs in continuous-time in a computer, and the supervision Matlab software runs on discrete-time on another computer; the link between the two PC's is done by serial port communication.

A sampling time of $T_s = 1s$ was used. All the values were normalized to the range [0;1].

## 4.2 Simulation Results

In Figure 4, are presented the signals obtained for an experiment in which is detected and isolated the fault F1. From top to bottom, the signals in this figure are: a1) the set-point for tank *T1*, the level *h1*, and the output predicted; a2) the flow *q1*; a3) the set-point for tank *T3*, the level *h3*, and the output predicted; a4) the residual *rg1*; a5) the residual *r1oe*, from the neural observer; a6) the residual *r3oe*, from the neural observer; a7) the qualitative level *h3d*; a8) the fault isolation signal.

The following table shows the detection delay for each fault, and the results are acceptable since the system has a slow dynamics.

*Table 2: Detection delay*

| *Fault* | *Detection delay [s]* |
|---|---|
| F1 | 31 |
| F2 | 32 |
| F3 | 14 |

The robustness of the FDI approach against set-point variations was also tested, for a range between {0.35;0.5}m, and a good performance (without false alarms) was obtained.

The experiments done with the faults F2 and F3 are shown in Figure 5, and Figure 6. In these figures, the same signals described in Figure 4 can be observed. The two faults, F2 and F3, were also well detected and isolated.

As can be observed in all simulations, the residuals and the signal *h3d* used for fault isolation (*Table 1*) reveals a good performance for FDI.

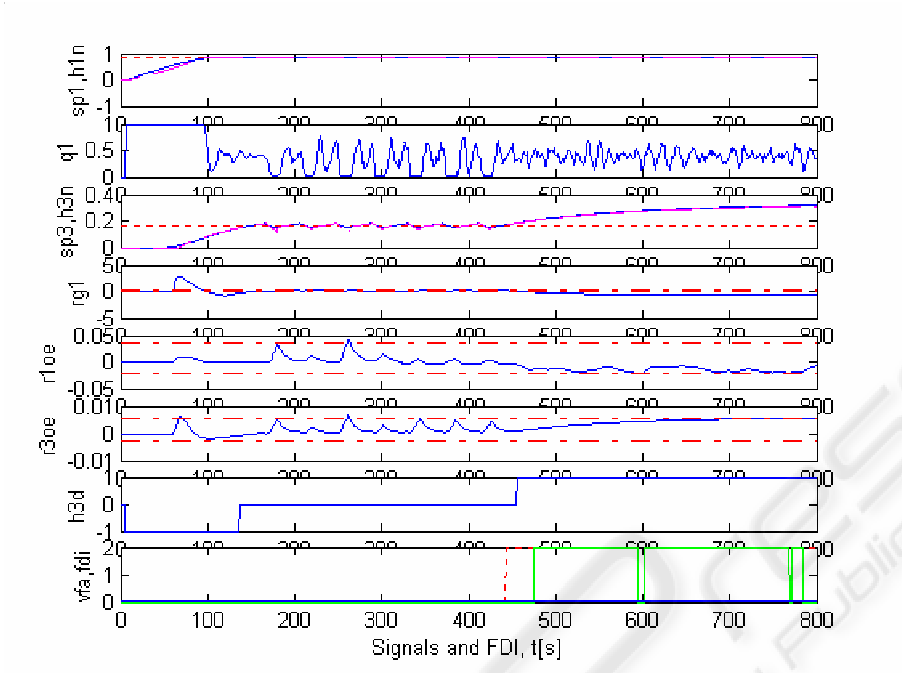


Figure 5: Signals for fault F2.

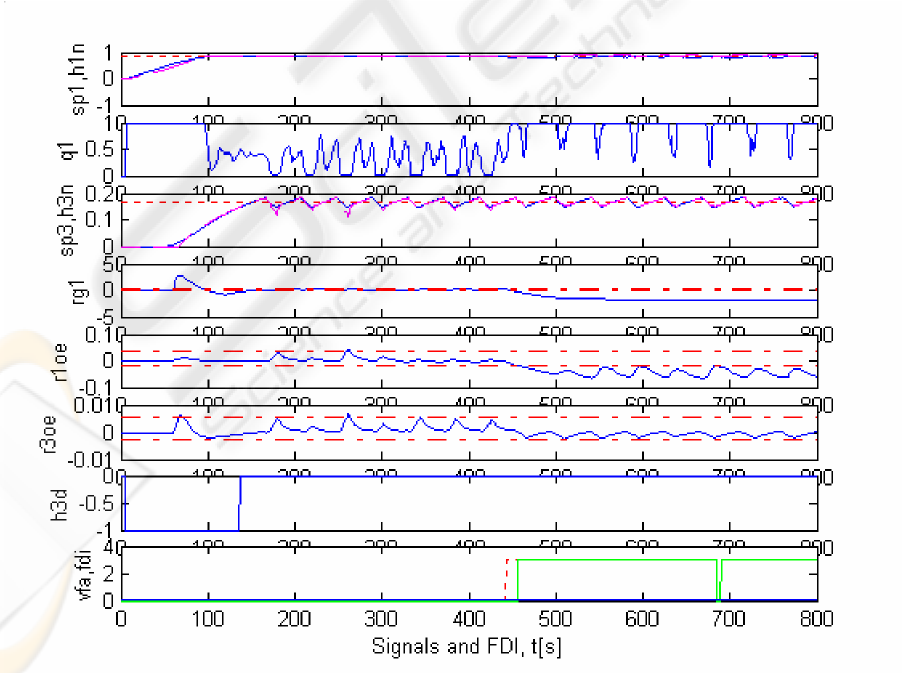


Figure 6: Signals for fault F3.

## 5 CONCLUSIONS

The paper proposes a combined approach to fault diagnosis (FDI) in dynamics systems. This approach integrates several FDI classical and intelligent (soft computing) methods.

All the available information must be use to perform FDI. An integration of process models and signals models improves the reliability of the FDI approach. A robust FDI system, able to be implemented in a practical problem, should combine both quantitative (numerical) and qualitative (symbolic) information. The soft computing techniques for FDI, like nonlinear neural observers, are particularly important and efficient as shown in this work. One great advantage of this type of approach is that a precise mathematical model is not required.

The proposed combined approach has been applied to a simulation model of the three-tank benchmark (a typical feed-water system), and the results shown good performance, and robustness against set-point variation.

The future work will concern to fault-tolerant control approaches via controller reconfiguration strategies, and the stability analysis of nonlinear neural observers.

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