Fuzzy Expert System for Residual Analysis

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ABSTRACT: *In industrial fields, decision making systems are very helpful. At critical situations such as failure occurrence, human being could not make the right decision at reasonable delays. This paper dealt with the conception and the development of an on line fuzzy system that simulates an hydraulic process and detects its abnormal behavior. Fuzzy logic is used to analyze residues of significant variables and to calculate certainty coefficient about generated alarms.*

Keywords: Component, Residue, Uncertainty, Fuzzy Sets, Fault Detection, Three Tank System

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1. Introduction

Decision support systems are developed widely in many application fields such as medical and industrial diagnosis, commercial domain, maintenance etc. This paper is centered especially on decision making in industrial fields. Fault detection is crucial operation in process surveillance. It is responsible qualifying the process state: normal or not. Decision makers used principally residual calculation and analysis to determine either a variable is following its reference. In fact, traditionally residual values must be around zero to be certain that our system is in normal situation.

However, in industrial diagnosis uncertainty could be the result of numerous sources: Any industrial plan is not essentially having an exhaustive mathematical model. Besides, with nonlinearities, even an existing model could not exactly describe the real system. Thus, mathematical methods depending on models may be founded on uncertain bases. Moreover, detecting real system state leans on observables variables and the effectiveness of its sensors, this is not always guaranteed.

Fuzzy logic is then used to qualify the residual values with linguistic terms and to enhance then uncertainty effects in one hand. In another one, conclusions about residues are then weighted with certainty factors.

The most common methodologies lean on weighting fault detection decisions with flexible certainty coefficients and choosing the most important one. First alternatives treated the problem with traditional tools as probabilitytheory and error interval analysis. These tools being unable to grasp all uncertainty facets [2], fuzzy sets were and still largely used to solve this issue [10] [11]. The first link between fuzzy logic and decision-making was introduced in [1]. It was based on the fact, that according to a criterion, good solutions are fuzzy sets. Besides, the best solution set is obtained from their intersection [3]. The most popular fuzzy sets approach, in decision-making, is the maximum ranking solutions. This method is natural when interpreting the fuzzy sets as flexible constraints. While uncertainty affects several domains and has many facets (randomness, fuzziness etc.), fields and applications concerned with this issue are, especially in the last decade, growing proving the efficiency of fuzzy logic use. Numerous works integrate fuzzy sets in monitoring and fault detection approaches [7] [6] [8]. In fact, fuzzy logic was integrated in different monitoring architectures: in neuro-fuzzy systems [12], fuzzy expert systems [12], fuzzy Petri nets, fuzzy residual generation methods etc. In one hand, fuzzy logic was used, essentially, in order to surmount uncertainty effects caused by the linguistic knowledge formulation of intelligent tools [5]. In another hand, fuzzy systems were integrated in defining variables and residues thresholds, to overcome model and sensors uncertainties [4].

To present this work three sections are to be considered. The first section dealt with research issue which is uncertainty and fault diagnosis. Next, the proposed approach architecture based on fault detection and alarm generation is detailed exhaustively. Finally, hydraulic system that could be encountered in many industrial fields constitutes the study case and the application of the methodology.

2. Research Issue

Based on the previous researches point of view, uncertainty could be found in different forms and at several levels creating uncertain environment for fault detection module. The aim of this work is to present an approved methodology to integrate fuzzy logic in fault detection systems to enhance their efficiency against uncertainties.

In an earlier work [12] and inspired by the research of Evsukoff [4] that was based on the analysis of residues and their variations through fuzzy system, we've tried to reduce the number of rules and to extend the uncertainty consideration. In this work, a support system is used to generate failures from residual values.

3. Fuzzy Residual Approach

We consider an approach which is based on residual analysis. Residuals were used in several works and had proven their efficiency, especially, when it concerns fault detection. In fact, when complete or partial quantitative model of the system exist, residuals becomes fast and efficient indicators about system variables behaviors. Hence, researches integrates this tool in monitoring decision making problems and usually affects certainty factors to alarm decisions based on residuals.

As figure 1 shows, our interest is not oriented to residual (r) generation but to its analysis. The FES architecture has two inputs r: residual and dr : residual derivative. And one output that traduces abnormal behavior severity ranged in [0-1] associated to process variable.

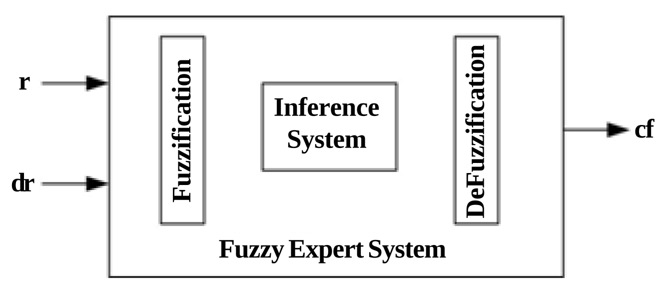

Figure 1. Fault detection architecture

The main idea is based on calculating at every step time, to each measured variable, residue r_j and its variation in time dr_j ($j \in \{1, 2, 3, \ldots\ldots m\}$ and m : number of measured variables). These variables are indicators about process state; Process behavior is optimum when no variables generate alarms.

3.1 Fuzzification

Let U_{rj} and U_{drj} be respectively the universe of discourse of physical variables r_j and dr_j. Figure 2 illustrates the ranges in which move r_j and dr_j. We should mention that a_1 and a_4 are criterion thresholds whereas a'_1 and a'_2 values are $a'_1 = 2.a_1$ and + $a'_2 = 2.a_4$ [4]. Linguistic variables r and dr are variables ranging respectively in sets of symbolic labels $A(r)$ and $B(dr)$ illustrated in equation 1. The terms describe qualitative value of magnitude of both residue and its variations.

$$A(r) = \{NN, N, Z, P, PP\}; B(dr) = \{N, Z, P\} \tag{1}$$

As figure 2 shows, five fuzzy sets are associated respectively with the elements of $A(r)$. Three fuzzy sets are associated respectively with the elements of $B(dr)$.

For each fuzzy set, the membership function is trapezoidal. The fuzzification process calculates the membership degrees. They vary in the interval [0-1] and they determine to what extend physical variables r and dr belong to fuzzy sets A_k and B_l.

We consider in our approach that fuzzy system output could be presented, only, by one linguistic label: *AL*. *AL* which is also associated with singleton, indicates that there is an abnormal attitude.

2. Inference Engine

Linguistic model relating variables r and dr to variable cf is written as rule base, relating the terms of $A(r)$ and $B(dr)$ to those of $cf(AL)$ in weighted rules, read as equation 2.

$$\text{If } r \text{ is } A_k \text{ and } dr \text{ is } B_l \text{ then } cf \text{ is } AL\ (\varpi) \tag{2}$$

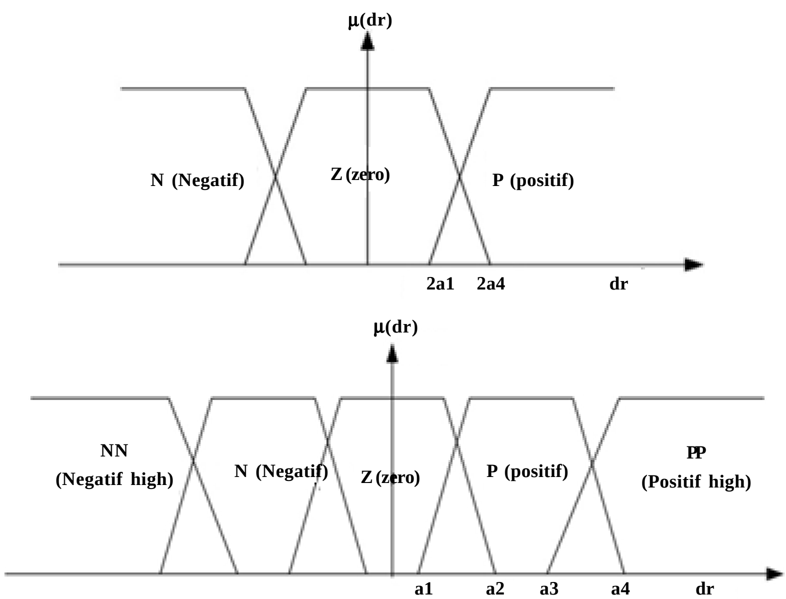

Figure 2. Membership functions of *r* and *dr*

r/dr	N		Z		P	
NN	AL	$\omega(1, 0.2)$	AL	$\omega(1, 0.2)$	AL	$\omega(0.8, 0.2)$
N	AL	$\omega(1, 0.2)$	AL	$\omega(0.6, 0.2)$	AL	$\omega(0.4, 0.2)$
Z	AL	$\omega(0.2, 0.2)$	AL	$\omega(0, 0.2)$	AL	$\omega(0.2, 0.2)$
P	AL	$\omega(0.2, 0.2)$	AL	$\omega(0.6, 0.2)$	AL	$\omega(1, 0.2)$
PP	AL	$\omega(0.8, 0.2)$	AL	$\omega(1, 0.2)$	AL	$\omega(1, 0.2)$

Table 1. New Inference Table

Table 1 summarizes the pattern that matches the two inputs *r* and *dr* to the output cf. It is composed of 15 weighted rules. Evsukoff [4] determinated the constant value of rules weight ϖ that are indicated in the table $\varpi \in \{0, 0.2, 0.4, 0.6, 0.8, 1\}$. These values reflect the degree of rule importance that is defined by experts

The inference table indicates that, for each combination of *r* and *dr*, one weighted rules is validated.

Besides, in order to raise uncertainty compensation, this work-study rules weight values ϖ. In fact, these values are constant traducing expert experience in fault detection. However, this experience is subjective and not always credible. Our approach proposes to weight rules using triangular functions centered on values presented by [4]. Rules credibility degree, presented by Figure 3, illustrates six triangular functions that are centered in ϖ value $w(\varpi, e) = triang(\varpi, \varpi - e, \varpi + e)$ with e fixed in $e = 0.2$. Table 2. is, then, the new adopted inference table of fuzzy system.

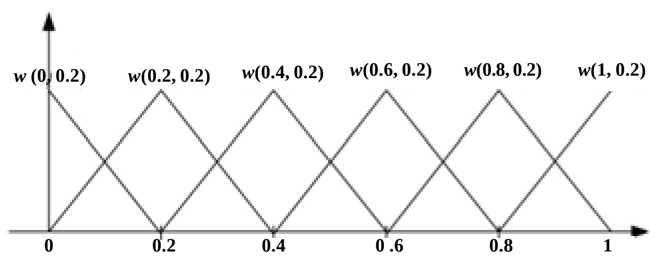

Figure 3. Triangular functions weighting rules

The inference, in this fuzzy system, is based on min-max method to calculate the membership function of the output. In fact, conjunction function, for AND method, is minimum, implication function is also minimum and aggregation function is max method. In this system output calculation, a crisp value is required. Thus, the defuzzification operation is requisite. In this approach, the *gravity centre* is the method adopted to get the crisp value traducing the severity of generated alarm, from the output membership function.

To have robust response and to guarantee consistency of the abnormality, final decision takes into account all the last sampling times. An alarm is generated when the minimum value of *CF* exceeded ε in *M* consecutive step times. Where (ε) is safety factor chosen according to required robustness. The system is declared in failure with a certitude coefficient that is *CF*.

The value that characterizes the alarm state of the variable *CF* is used to weight the alarm generation. In fact, the weight attributed to the system state (normal or abnormal) *CF* is interpreted as indicator about the credibility of the fault detection decision. Hence, the fuzzy system is used to minimize uncertainty caused by nonlinearities and non-exhaustively of quantitative model in one hand. The sensor imperfection information and subjective choice of criterion thresholds are moderated in another hand. In our approach we've adopted the inference system presented by Evsukoff [4] to evaluate and analyze residues variation in time. The weighted final decision about the system state is carried out through new deffuzification approach based on the *M* last sampling time to guarantee the persistence and robustness of failures.

4. Study case

The system under consideration is a pilot plant of the research unit: *System analysis and command* located in ENIT (National Engineer Institute of Tunisia). This system is composed of three interconnected cylindrical tanks, two pumps, six valves, pipes, water reservoir in the bottom, measurement of liquid levels and other elements. The pumps pump water from the bottom reservoir to the top of the left and right tanks. A schematic diagram of the considered system is shown by figure 4.

While tanks 1, 2 and 3 are identical with cross section *S* and maximum fluid level l_{max}, Drain tank is characterized with cross section S_d and maximum fluid level l_{dmax}. Tanks 1 and 3 are coupled with tank 2 by two AON (*all-or-none)* valves with cross section S_n and outflow coefficients. Two proportional valves *EV*1 and *EV*2 directly connected to a pump, with highest possible flow rate denoted q_{max} supply tanks 1 and 2. Three sensors are installed to measure the three levels l_1, l_2 et l_3. The experimental plant that is equipped with sensors and actuators, communicates via data acquisition system with a personal computer.

Using the mass balance equations the system can be described by the following equations system:

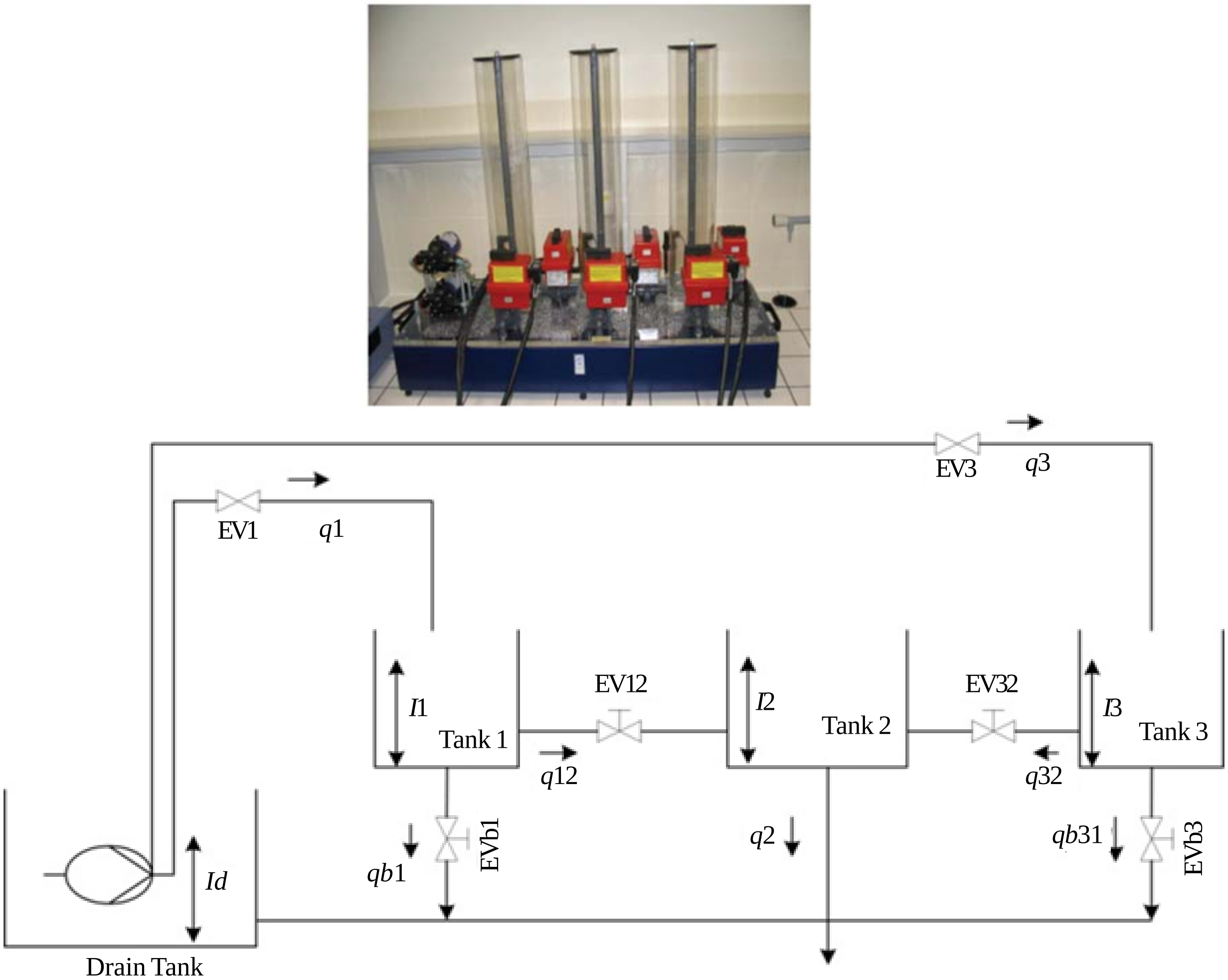

Figure 4. Three tank system representation

$$\begin{cases} q_1(t) - q_{12}(t) - q_{b1}(t) = S.\dfrac{dl_1(t)}{dt} \\ q_3(t) - q_{32}(t) - q_{b3}(t) = S.\dfrac{dl_3(t)}{dt} \\ q_{12}(t) - q_{32}(t) - q_2(t) = S.\dfrac{dl_2(t)}{dt} \end{cases} \quad (3)$$

With: command flows q_1 and q_3 are respectively the income flows of tanks 1 and 3, q_{bi} are bleeding flow from tank i ($i \in$ to $\{1, 2, 3\}$) to drain tank. Finally, q_{12} and q_{32} represent, respectively, the fluid flow rate from tank 1 to tank 2 and from tank 3 to tank 2. These unmeasured flow rates can be determined using the Torricelli law as:

$$\begin{cases} q_{12}(t) = S_n.\, \mu_{12}.\, l_1(t) - l_2(t))\, \sqrt{2.g|l_1(t) - l_2(t)|} \\ q_{32}(t) = S_n.\, \mu_{32}.\, l_3(t) - l_2(t))\, \sqrt{2.g|l_3(t) - l_2(t)|} \\ q_2(t) = S_n.\, \mu_{20}.\sqrt{2.g.l_2(t)} \end{cases} \quad (4)$$

The purpose is to control the system around an operating point $(u_0,\ y_0)$ which is fixed to :

$$u_0 = (0.35, 0.375)^T \times 10^{-4} m^3 s^{-1}\ and\ y_0 = (0.40, 0.295, 0.20)^T\ m$$

The system is linearized around this operating point using Taylor expansion. The linearized system is described by a linear space state:

Now if we consider that = $[l_1\ l_2\ l_3]^T$ is the output vector, $e = [q_{b1}\ q_{b3}]^T$ and $u = [q_1\ q_3]^T$ is the command vector, the system can be written in linear state space:

$$\begin{cases} \dfrac{dx(t)}{dt} = A.x(t) + B.u(t) + k.e(t) \\ y(t) + C.x(t) \end{cases} \tag{5}$$

Where $G_{f1} = \dfrac{K_{f1}}{2\sqrt{L_{10} - L_{20}}}$, $G_{f3} = \dfrac{K_{f3}}{2\sqrt{L_{30} - L_{20}}}$ and $G_{f2} = \dfrac{K_{f2}}{2\sqrt{L_{20}}}$, we could have:

$$A = \begin{pmatrix} \dfrac{-G_{f1}}{S} & \dfrac{G_{f1}}{S} & 0 \\ \dfrac{G_{f1}}{S} & \dfrac{-(G_{f3}+G_{f2}+G_{f1})}{S} & \dfrac{G_{f3}}{S} \\ 0 & \dfrac{G_{f3}}{S} & \dfrac{-G_{f3}}{S} \end{pmatrix}$$

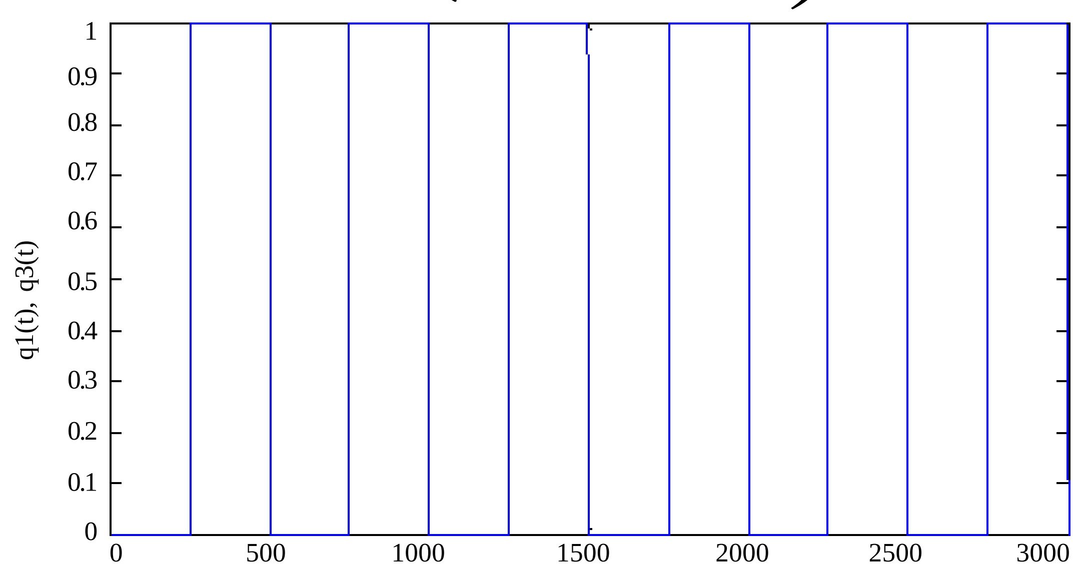

Figure 5. Nominal control inputs $q1(t)$ and $q3(t)$

$$B = \begin{pmatrix} \dfrac{1}{S} & 0 \\ 0 & \dfrac{1}{S} \\ 0 & 0 \end{pmatrix}, \quad K = \begin{pmatrix} -\dfrac{1}{S} & 0 \\ 0 & -\dfrac{1}{S} \\ 0 & 0 \end{pmatrix} \quad C = \begin{pmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{pmatrix} \tag{6}$$

Variable	Symbol	Value
Tank cross section area	S	$0.015 \quad 4m^2$
Inter tank cross section area	S_n	$5{\times}10^{-5}m^2$
Outflow coefficient	μ_{20}	0.6
Maximum flow rate	$\mu_{20} = \mu_{23}$	0.5
Maximum level	$q_{1max} = q_{3max}$	$1.5\ m^3.\ s^{-1}$
	$l_{1max} = l_{2max} = l_{3max}$	$0.62m$

Table 2. System characteristics

This process modeling is, then, estimated to be:

$$A = \begin{pmatrix} -0.0111 & 0.0111 & 0 \\ 0.0111 & -0.0307 & 0.01166 \\ 0 & 0.01166 & -0.01166 \end{pmatrix},$$

$$B = \begin{pmatrix} 64.94 & 0 \\ 0 & 64.94 \end{pmatrix},\ K = \begin{pmatrix} -64.94 & 0 \\ 0 & -64.94 \\ 0 & 0 \end{pmatrix}\ C = \begin{pmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{pmatrix} \tag{7}$$

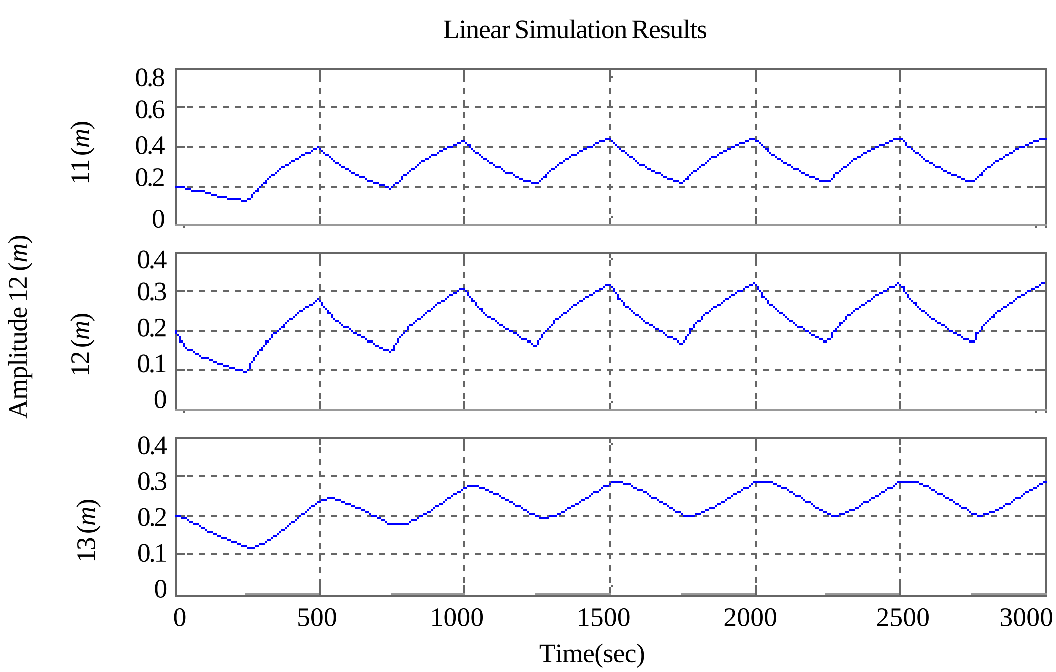

Figure 6. Nominal control outputs l1(t), l2(t) and l3(t)

4.1Fault Free Simulation

Figure 5 and figure 6 are respectively nominal control inputs and outputs variations of estimated state model simulated for 3000s.

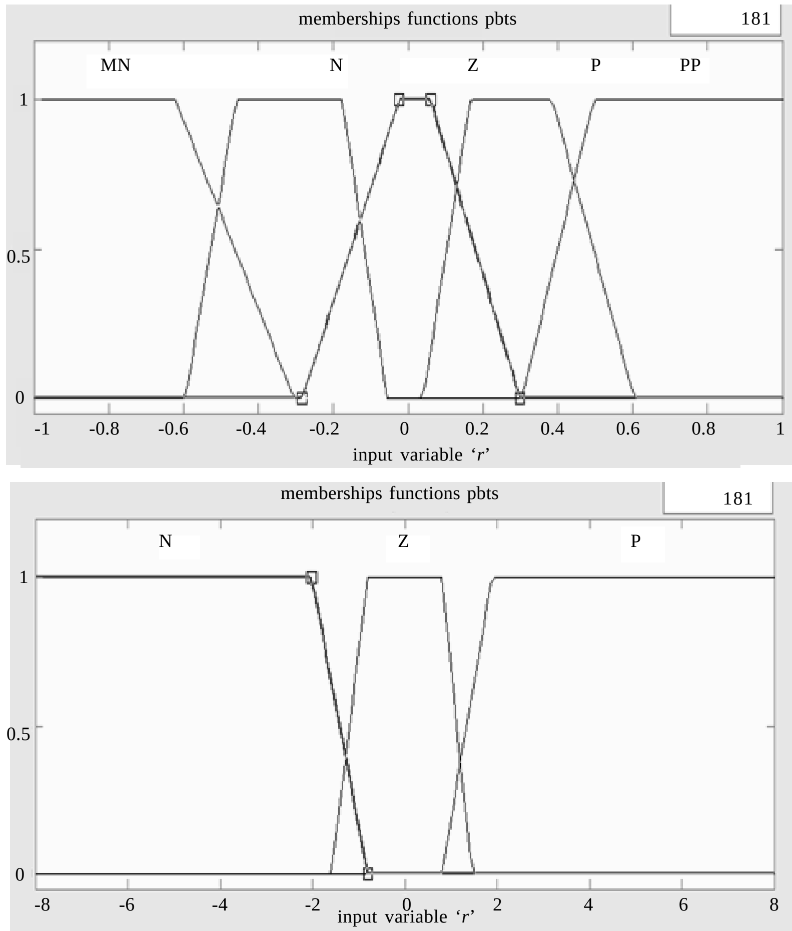

Figure 7. *r* and *dr* memberships functions

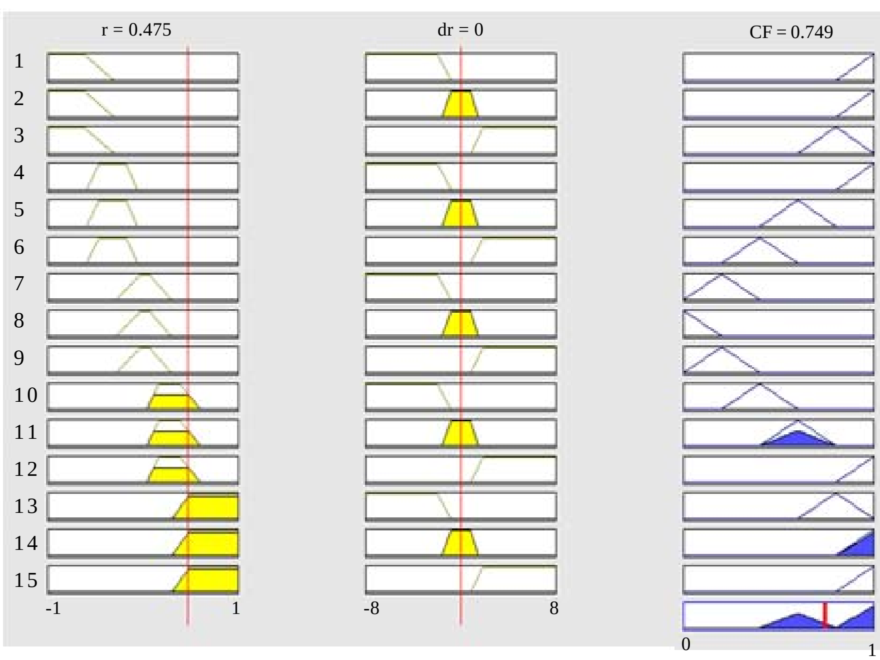

Figure 8. Example of D calculation

Taking into account thresholds of the three simulated outputs, limits of residue (r) and its variations (dr) memberships are illustrated by figure 7. These values lead to a certitude coefficient that is represented by figure 7 and figure 8.

Knowing that the value of the fuzzy system output is a singleton, the output will be calculated through the projection on triangular functions that are weighting the rules. The 3D representation of *CF* variation indicates that: with r values around zero, CF is almost minimal but it reaches its maximum when r and dr are important.

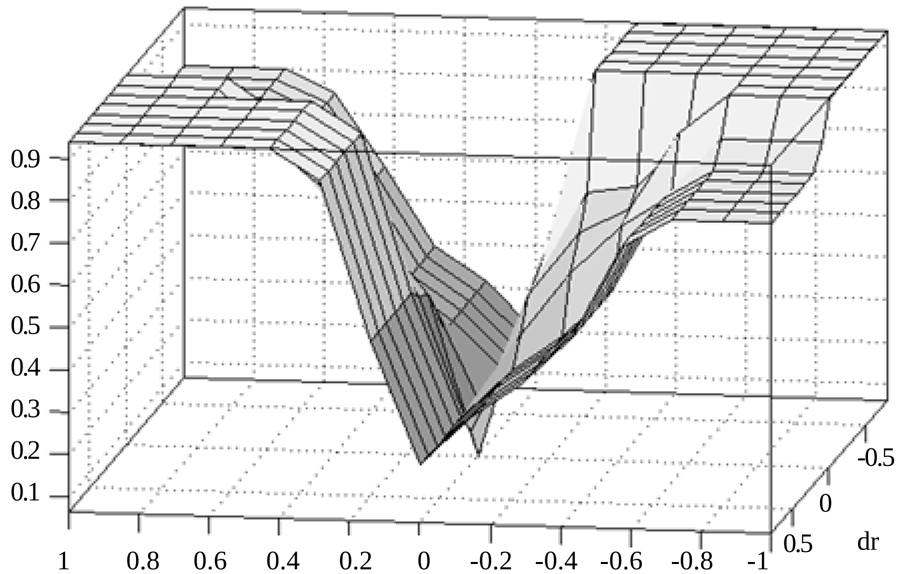

Figure 9. 3D representation of D values

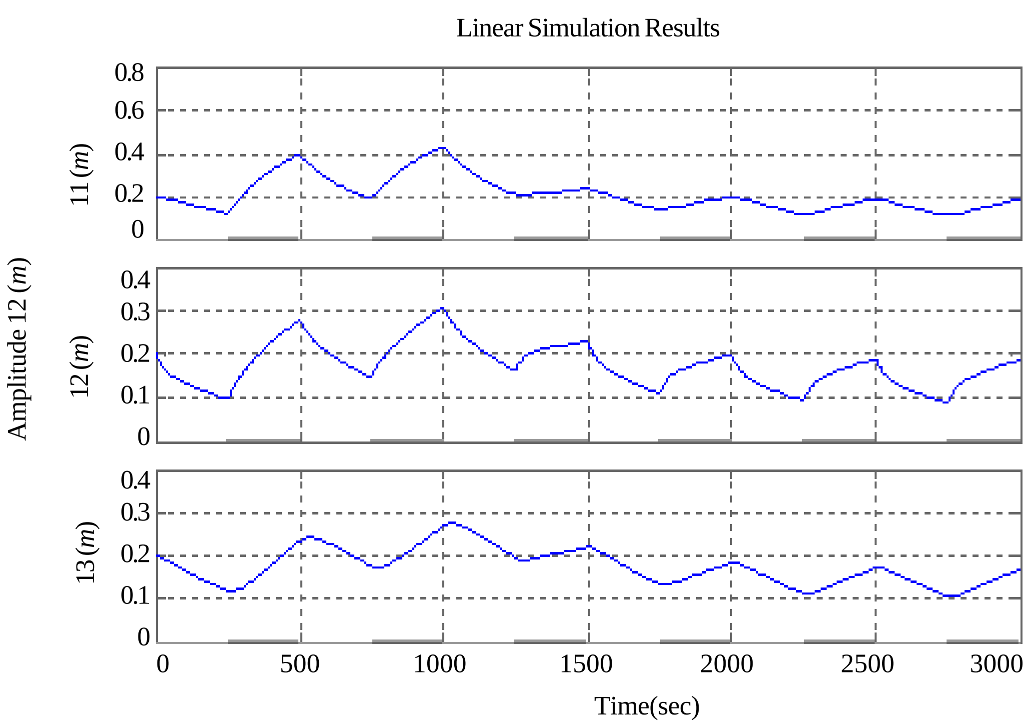

Figure 10. Outputs under pump 1 multiplicative fault ($\alpha_1 = 0.1$)

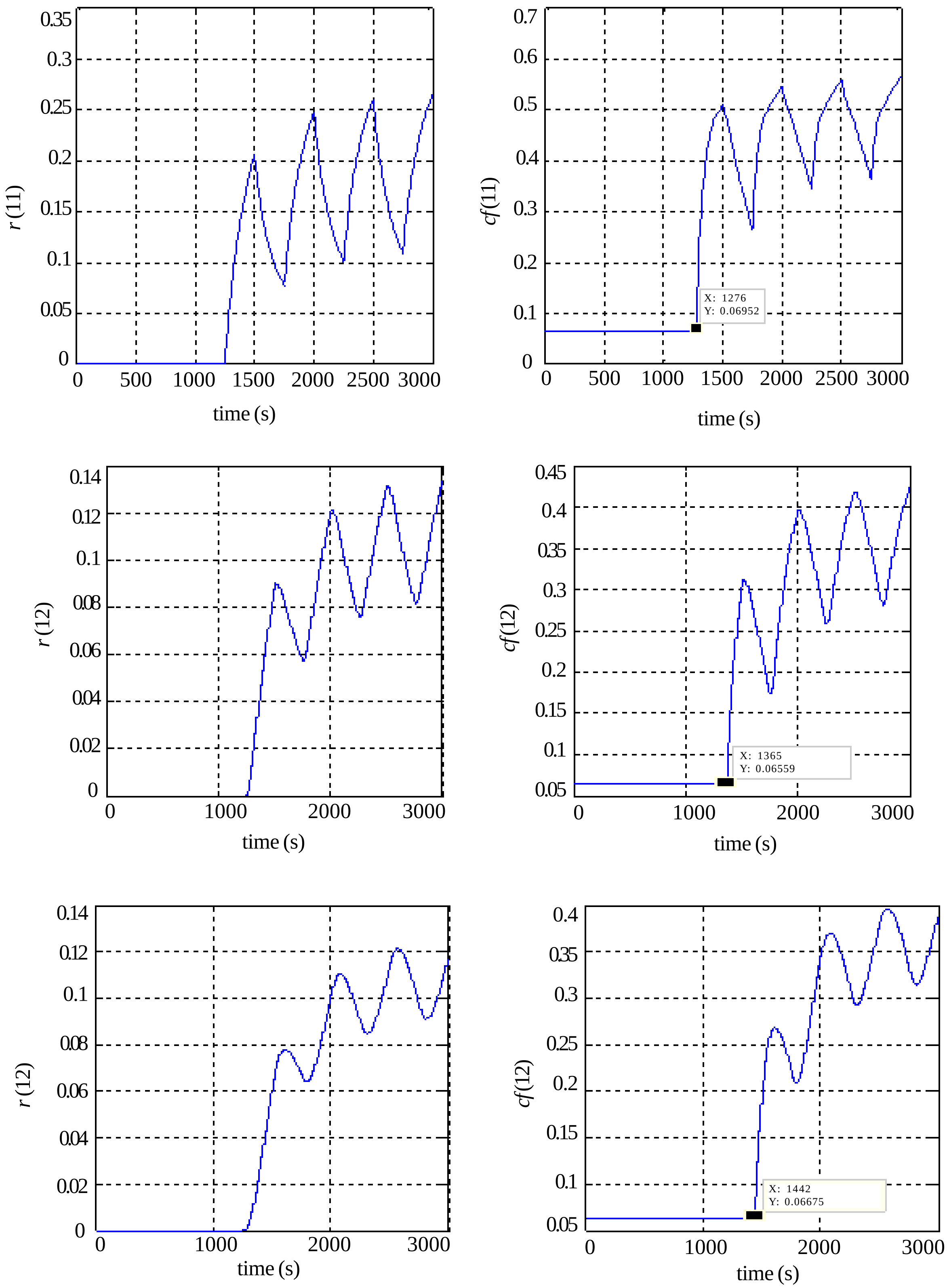

Figure 11. *ri* and CF(*ri*) under pump 1 multiplicative fault ($\alpha_1 = 0.1$)

Taking into account thresholds of the three simulated outputs, limits of residue (r) and its variations (dr) memberships are illustrated by figure 7. These values lead to a certitude coefficient that is represented by figure 7 and figure 8.

Knowing that the value of the fuzzy system output is a singleton, the output will be calculated through the projection on triangular functions that are weighting the rules. The 3D representation of CF variation indicates that: with r values around zero, CF is almost minimal but it reaches its maximum when r and dr are important.

In this work, we consider that many additive or multiplicative faults can affect the system due to material aging or to abnormal situations. These faults can be caused by actuators or sensors.

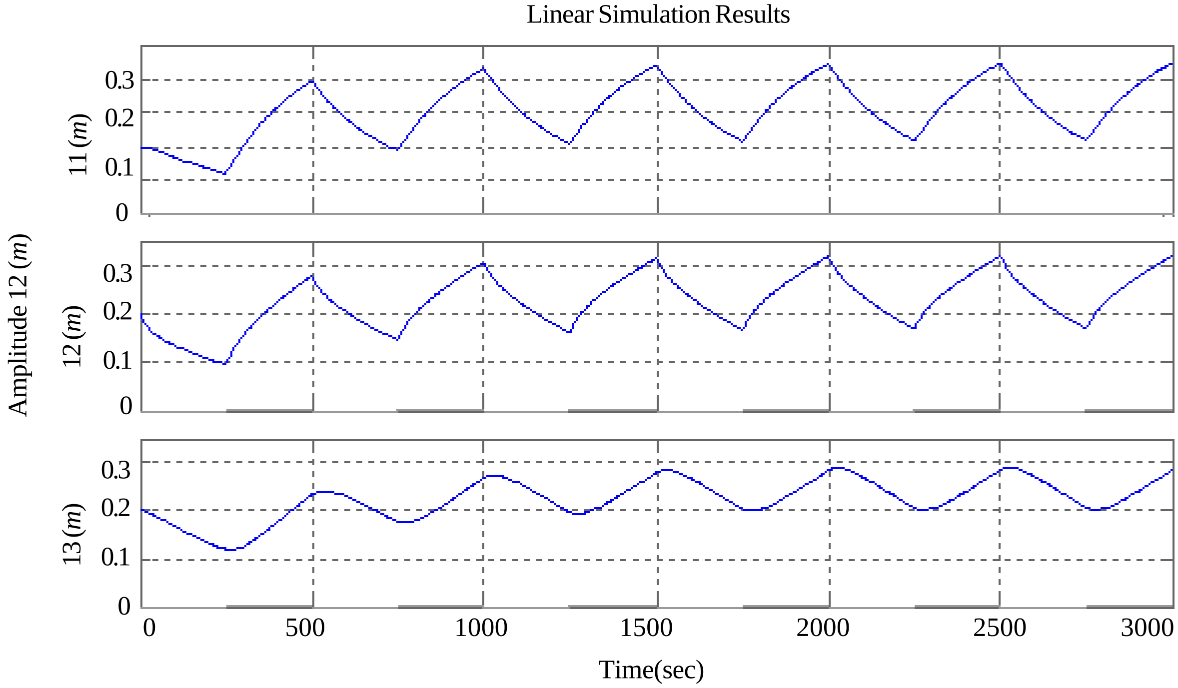

Figure 12. outputs under sensor 2 multiplicative fault ($\beta_2 = 0.2$)

4.2 Actuator Fault

We consider, in this paper, actuator faults that are represented in paper [9]. An actuator (i) fault can be represented by additive and/or multiplicative faults as follows:

where u_i and u_i^f represent the normal and fault control inputs of the actuator i. u_0 is a constant offset and $0 < \alpha_i < 1$ is a gain degradation of actuator i.

First, the gain degradation of pump1 is considered and at instant 1000 s it becomes equal to 0.1. The dynamic behavior of the system is illustrated by figure 10.

The fault detection system response is represented by coefficient CF evolution. We can see that coefficient CF (l1) is the most important and that it was activated 271 s after fault occurrence.

The CF dynamic behaviour is completely depending on residual and its variation.

4.3 Sensor Fault

We consider, in similar way, sensor j faults that are represented as follows:

$$y_{ij}^f = B_J \cdot y_j + y_{j0}$$

where y_{j0} and y_j represent the normal and fault control actions of the j^{th} sensor, respectively. y_{j0} is a constant offset and $0 < \beta_i < 1$ denotes a gain degradation.

In a similar way, we simulate a multiplicative fault occurring on sensor 2. Figure 12 and figure 13 are the illustrations of system behavior and CF calculation.

This paper gives a new method to analyze residuals based on fuzzy logic. In fact, the integration of fuzzy logic in fault detection provides more effectiveness and reliability to alarm generation.

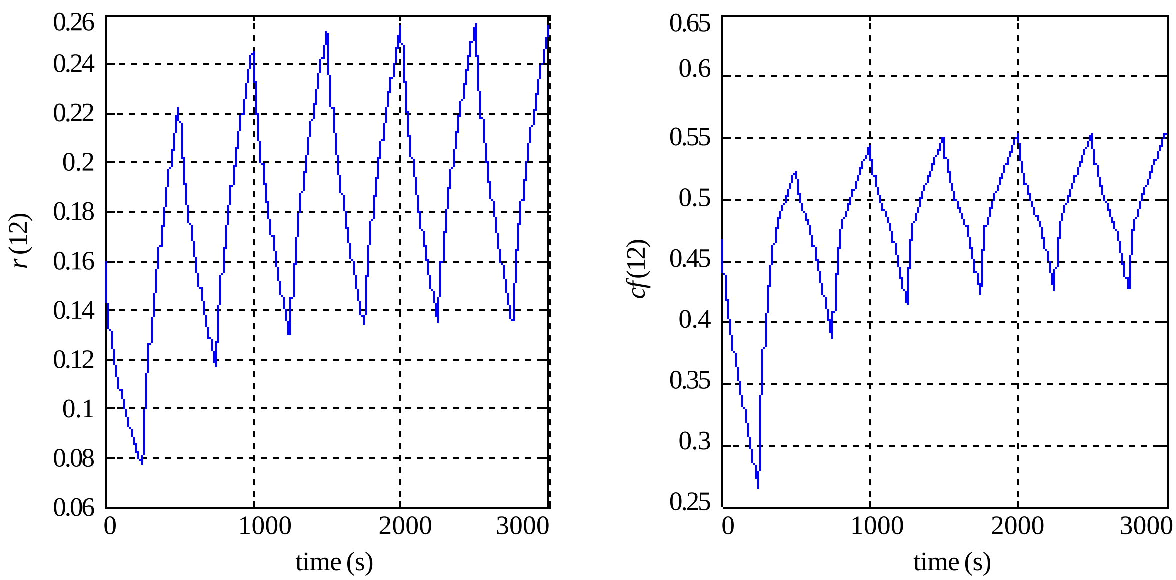

Figure 13. *ri* and CF(*ri*) under sensor 2 fault ($\beta_2 = 0.2$)

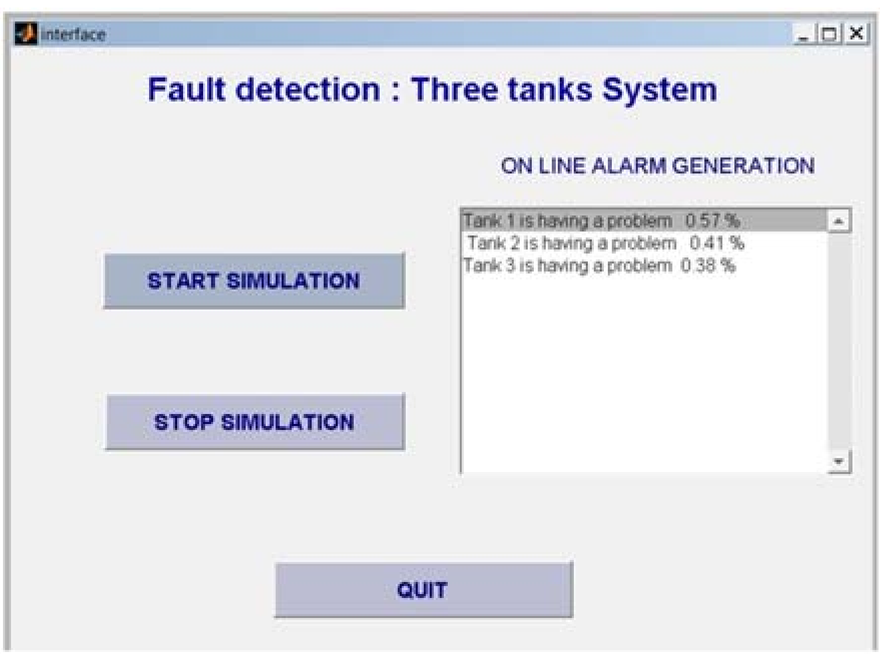

Figure 14. System Interface pump 1 multiplicative fault ($\alpha_1 = 0.1$)

4.4 Alarm Generation

A simple user interface is developed using Matlab GUI and simulink.

In this case, hydraulic process presents three measured continuous variables (level heights) that could help to locate the possible failure.

When *cf* corresponding to a variable exceeds its limit, the variable is declared in failure. For example in the case illustrated by figure 14, the three tanks were touched by the actuator fault but we could remark that the certainty factor cf is the most important in tank 1 which could give an idea about the root cause of the failure. Obviously, a diagnosis operation is needed to identify pump1 as root cause.

5. Conclusion

This paper gives a new method to analyze residuals based on fuzzy logic. In fact, the integration of fuzzy logic in fault detection provides more effectiveness and reliability to alarm generation. Based on the inference presented by Evsukoff, our methodology gets its originality from the use of triangular functions to weight rules instead of fixed values.

The application on a three tank system proves a fast and efficient response to simulated faults rather sensor or actuator ones. And the FES calculates a coefficient which is sensitive to failure origins.

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