Fuzzy Evidential Approximate Reasoning Scheme for fault diagnosis of complex processes

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Abstract

In this paper, a fuzzy evidential model based fault detection and diagnosis method is presented for the supervision of nonlinear and complex processes. The powerful multi-modeling methodology is used to detect changes of the current process behavior and to generate analytical symptoms. The diagnosis task is accomplished by fuzzy evidential approximate reasoning scheme to handle different kinds of uncertainty that are inherently present in many real word processes, and to make decision under conflicting data. The validity of the method is illustrated on the well-known benchmark of three tanks and different faults can be detected and isolated continuously, over all ranges of operation.

Keywords: parity equations, nonlinear dynamic processes, evidential approximate reasoning, conflict management.

1 Introduction

The development of process supervision and model-based fault diagnosis began at various places in the early of the 1970s. This method has receiving more and more attention over the last two decades. This is mainly due to the increasing demands of better protection of the environment against pollution and on reliability and safety of technical processes. Several approaches have been developed, including traditional signal analysis as well as model-based techniques. The diagnostic system serves several purposes: it identifies the optimal decision boundaries between the different faulty states with as many details as possible even in the presence of noise and uncertainties. It should treat different symptoms in a coherent and transparent way for users to simplify the traceability of decision making. Common diagnosis approaches can be split in two basic categories. The first one includes fault symptom trees and fuzzy rule bases that use explicit knowledge to treat heuristic symptoms, which are mostly obtained by inspections through a human operator and by stating the statistics history of the monitored process. The appropriate heuristic rules for the fault diagnosis are then gathered through consulting experts. The second category is based on measurement data to generate analytical symptoms. Recently, some approaches integrating both heuristic and analytical symptoms have also gained an increasing attention.

A crucial problem arises when using explicit knowledge base (like fault symptom trees or fuzzy rule bases) is the lack of sufficient information and the existence of uncertainty. Sometimes, only parts of such knowledge base exist, or they are tedious to derive. On the other hand, most of the data-driven techniques neglect the capacity of human interaction and knowledge that can improve the design. Therefore, the diagnosis system can be improved when taking into account aspects
like transparency, simplicity, uncertainty and conflict management. To overcome the problem of precision and accuracy in FDD, various approaches based on fuzzy logic have been also suggested. However, the fuzzy logic approach is not only required on its own, but as a framework for combining different paradigms. More specifically, quantitative model-based and soft-computing are combined to exploit the benefit of each.

In this paper, we propose a method for the diagnosis of dynamic nonlinear processes using the multi-modeling methodology for symptom generation and a fuzzy-evidential approximate reasoning scheme. The rest of this paper is organized as follows: Section 2 gives a brief overview of fault detection and diagnosis. Section 3 describes the multi-modeling methodology. Section 4 presents the fuzzy evidential approximate reasoning for fault diagnosis. Experimental results concerning the well-known benchmark of three tanks are presented in section 5. Finally, some concluding remarks as well as some possible improvements are given in section 6.

2 Overview of Fault detection and diagnosis

Different approaches for fault detection and diagnosis using mathematical models have been initiated and developed from the early seventies to now, see [4], [7], [8]. They can be divided in two categories. The first one is based on state estimation and includes detection filter, parity space approaches as well as observer-based methods. Parameter estimation techniques [7] belong to the second family. The general scheme of process model-based fault detection and diagnosis includes the following two stages:
- symptom generation
- fault diagnosis

The first one uses input-output observations and some mathematical relationships of the process under consideration to elaborate a set of residuals or symptoms which enables fault detection and isolation. In the fault diagnosis stage, the task consists of the detection of the type of fault with as many details as possible such as the fault size, location and time of detection. In model-based fault detection and diagnosis, the most important task is the generation of residual signals which are independent of the disturbances.

3 Multi-modeling strategy

The major motivation for the multiple modeling methodology is that locally there are less relevant phenomena, and interactions are simpler. In this context, the so called Takagi-Sugeno (TS) fuzzy systems are proposed because they are able to approximate nonlinear relationships with good properties. Assume we have a complex nonlinear multi-input and multi-output (MIMO) relationship where \( x = [x_1, \ldots, x_n]^T \in \mathcal{X} \subset \mathbb{R}^n \) is the vector of input variables and \( y \in \mathcal{Y} \subset \mathbb{R}^m \) is the vector of output variables. The overall output is defined as:

\[
\hat{y}_j(x) = \frac{\sum_{i=1}^{H} f_{ij} \phi_i}{\sum_{i=1}^{H} \phi_i} \quad (1)
\]

where, \( j = 1, 2, \ldots, m; \quad i = 1, 2, \ldots, H \) and \( l = 1, 2, \ldots, n; \)

\[
\phi_i = \prod_{l=1}^{n} \exp \left\{ -(x_l - c_{il})^2 / (\sigma_{il})^2 \right\} \quad (2)
\]

Here, we assume that \( c_{il} \in \mathcal{X}_i, \sigma_{il} > 0 \) and \( f_{ij} \in \mathcal{Y}_j \), where \( \mathcal{X}_i \) and \( \mathcal{Y}_j \) are the variation domains of the input \( x_i \) and output \( y_j \), respectively. The learning process is performed in two phases. Firstly, a clustering algorithm [6] is used to find a coarse model that roughly approximates the underlying input-output relationship. Secondly, parameter optimization procedure is performed for a better tuning of the initial structure. In principle, once an appropriate structure is identified, the learning task can be accomplished by any suitable training algorithm such as the standard backpropagation algorithm (BPA). However, because of slow convergence speed of pure BPA, in the following a more efficient training method, namely the combination of gradient descent with least squares optimization procedure will be used.
3.1 Parameter optimization procedure

The parameters obtained by the identification procedure can be optimized or fine tuned by a variant of gradient descent optimization techniques. This is achieved by an iterative hierarchical two stage optimization algorithm. In the forward stage, with the membership functions (MF’s) being constant, the functional models $f_{ij}$, $i = 1, \ldots, H$ and $j = 1, \ldots, m$ are identified by solving a least squares problem. Then, in the backward stage, the functional models are fixed and the parameters of the membership functions $c_{il}$, $\sigma_{il}$, $i = 1, \ldots, H$; $l = 1, \ldots, n$ are updated by an effective nonlinear gradient-descent (GD) optimization technique, which requires the computation of the derivatives of the objective function to be minimized with respect to the parameters $c_{il}$ and $\sigma_{il}$.

The optimization algorithm uses a variable step learning rates. Given a set $D = \{(x^p, d^p)\}_{p=1}^N$, such that $x^p \in \mathcal{X} \subset \mathcal{R}^r$, $d^p \in \mathcal{Y} \subset \mathcal{R}^m$; the objective is to find sub-systems $\hat{y}_j(x^p)$ in the form of (1), such that the mean squared error (MSE) function

$$ E = \frac{1}{2} \sum_{j=1}^m \left( \hat{y}_j - d^p_j \right)^2 $$

is minimized. The problem is reduced to the adjustment of the $f_{ij}$, and the mean ($c_{il}$) and variance $\sigma_{il}$ of the ellipsoidal functions, so that the MSE is minimized.

Now it can be seen that the output $\hat{y}_j$, and hence $E$, depends on $c_{il}$ and $\sigma_{il}$ only through $\phi_i$, where $\hat{y}_j$, $f_{ij}$, $b$ and $\psi_i$ are represented by the following equations:

$$ \hat{y}_j = \frac{1}{H} \sum_{i=1}^H f_{ij} \psi_i $$

(4)

$$ \psi_i = (\phi_i/b) \text{ and } b = \sum_{i=1}^H \phi_i $$

(5)

**Derivatives of $E$ w.r.t $c_{il}$ and $\sigma_{il}$**

$$ \frac{\partial E}{\partial c_{il}} = \frac{\partial E}{\partial \phi_i} \frac{\partial \phi_i}{\partial c_{il}} = \sum_{j=1}^m \left( \frac{\partial E}{\partial \hat{y}_j} \frac{\partial \hat{y}_j}{\partial \phi_i} \right) \frac{\partial \phi_i}{\partial c_{il}} $$

(6)

Finally, the results of the chain rules are written as follows:

$$ \frac{\partial E}{\partial c_{il}} = A \cdot \left\{ 2 \cdot \phi_i \cdot (x^l - c_{il}) / (\sigma_{il})^2 \right\} $$

(8)

$$ \frac{\partial E}{\partial \sigma_{il}} = A \cdot \left\{ 2 \cdot \phi_i \cdot (x^l - c_{il})^2 / (\sigma_{il})^3 \right\} $$

(9)

with $A = \left( \sum_{j=1}^m (\hat{y}_j - d^p_j) \cdot (f_{ij} - \hat{y}_j) / b \right)$. 

4 Fuzzy evidential approximate reasoning

4.1 Background

Evidence theory, also known as Dempster-Shafer theory [2] can be seen as a generalization of possibility theory (as used in fuzzy set theory) and also statistical probability theory. It is concerned with bodies of evidence, which are assignments of weights to crisp events such as fault occurrence.

Given a domain $\Omega$ of possible events, a basic belief assignment (BBA) $m$ is a mapping

$$ m : 2^\Omega \rightarrow [0, 1] $$

(10)

where $2^\Omega$ is the power set (set of all subsets) of the domain. For any element $A \in 2^\Omega$, the basic belief assignment $m(A)$ gives the amount of evidence that supports that event and no other. Basic belief assignments are required to follow the axioms:

$$ m(\emptyset) = 0 $$

$$ \sum_{A \in \Omega} m(A) = 1 $$

(11)

The first of these states that evidence cannot exist that supports no element of the domain. This axiom can always be fulfilled if the domain is chosen carefully. The second constraint ensures normalization of evidence. A body of evidence can be completely specified by two fuzzy measures, belief and plausibility, which are given by:

$$ Bel(A) = \sum_{A \subseteq B : B \neq \emptyset} m(B) $$

(12)
\[ Pl(A) = \sum_{A \cap B \neq \phi} m(B) \quad (13) \]

respectively. The set \( B \) is defined on the same domain as \( A \). Belief can be interpreted as the total evidence directly supporting the event \( A \). Plausibility is the amount of evidence not contradicting the same conclusion, that is

\[ Pl(A) = 1 - Bel(\bar{A}) \quad (14) \]

In addition to this evidential interpretation, plausibility and belief may also be regarded as the upper and lower probabilities of an event with

\[ Bel(A) \leq P(A) \leq Pl(A) \quad (15) \]

and consequently the likelihood of a hypothesis is represented as an interval \([Bel(A), Pl(A)]\), a subset of the interval \([0, 1]\). In probabilistic terms one can say that the probability of \( A \) is bounded between \( Bel(A) \) and \( Pl(A) \). The uncertainty of \( A \) is given by \( u(A) = Pl(A) - Bel(A) \). The limit case \( u(A) = 0 \) for all hypothesis coincides with the results of Bayesian theory. With complete information, the three measures converge. However, if information that is required for making a diagnosis is unreliable or missing then the difference between belief and plausibility increases. In the extreme case of perfect ignorance belief becomes zero and plausibility one.

4.2 Dempster’s rule of combination

In many cases, the combination or the fusion of different information sources is an interesting solution to obtain more relevant information. Evidence theory provides a coherent framework for integrating different information sources. In fact, for a given number of BBA’s \( m^1 \) obtained from different information sources \( S^1 \), the use of a combination rule provides combined masses summarizing the knowledge of the different sources. These belief masses can then be used for decision making with the advantage of the total knowledge contained in the belief functions given by each source.

For two information sources \( S^1 \) and \( S^2 \), the induced BBA’s \( m^1 \) and \( m^2 \), can be combined by the so-called Dempster’s rule of combination to provide a new BBA \( m = m^1 \oplus m^2 \), called the orthogonal sum of \( m^1 \) and \( m^2 \), and defined as:

\[ m(A) = \frac{\sum_{B \cap C = A} m^1(B)m^2(C)}{1 - m(\phi)} \quad \forall A \subseteq \Omega \quad (16) \]

where the quantity in the numerator corresponds to the conjunctive rule of combination and the mass \( m(\phi) \) assigned to the empty set is defined by

\[ m(\phi) = \sum_{B \cap C = \phi} m^1(B)m^2(C) \quad (17) \]

In the above equations, the mass \( m(\phi) \) reflects the conflict between the two sources \( S^1 \) and \( S^2 \). Assuming the normality of the BBA’s \( m(\phi) = 0 \), the use of this rule is possible only if \( m^1 \) and \( m^2 \) are not totally conflicting, i.e., if there exist two focal elements \( B \) and \( C \) of \( m^1 \) and \( m^2 \) satisfying \( B \cap C \neq \phi \). Let us denote the belief function resulting from the combination of \( K \) information sources as:

\[ m = m^1 \oplus \cdots \oplus m^i \cdots \oplus m^K \quad (18) \]

where \( \oplus \) represents the operator of combination.

4.3 Symptom evaluation

The starting point of constructing a diagnosis rule-based system is to collect IF-THEN rules from human experts or based on domain knowledge. Formally, a rule-based model is represented as:

\[ R = \{S, A, D, F\} \]

where \( S = \{S_k; k = 1, \ldots, T\} \) is the set of antecedent symptoms, with each of them taking values (or propositions) from an array of finite sets \( A = \{A_1, \ldots, A_T\} \). \( A_k = \{A_{kj}; j = 1, \ldots, J_k = |A_k|\} \) is a referential set of values for a symptom \( S_k(k = 1, \ldots, T) \), and the values in \( A_k \) (e.g. \( A_{kj} \)) is referred to as referential values. The array \( \bar{S} = \{S_1, \ldots, S_T\} \) defines the list of finite conditions, representing the elementary states of the problem domain, which may be linked by AND or OR.
connectives. $D = \{D_j, j = 1, \ldots, N\}$ is the set of all consequents, which can be conclusions. $F$ is a logical function, reflecting the relationship between conditions and their associated conclusions. More specifically, the $i$th rule in a rule-base in forms of a conjunctive IF-THEN rule can be written as:

$$R^i : IF S_1 is A^i_1 and \ldots S_T is A^i_T, THEN D_i,$$

(19)

$A^i_j (j = 1, \ldots, T_i)$ is the referential value of the $j$th antecedent symptom used in the $i$th rule and $T_i$ is the number of the antecedent symptoms in the $i$th rule. $D_i (\in D)$ is the consequent in the $i$th rule.

In order to take into account the belief degrees of a rule, symptom weights and rule weights, the rule given in (19) is extended to a so called uncertain rule using the belief structure, where all possible consequents are associated with belief degrees. A collection of uncertain rules consists of a rule-base with a belief structure as follows:

$$R^i : IF S_1 is A^i_1 and \ldots S_T is A^i_T, THEN \{(D_1, u^i_1), \ldots (D_N, u^i_N)\}$$

(20)

where $\left(\sum_{j=1}^{N} u^i_j \leq 1\right)$, with a rule weight $\alpha^i$ and symptom weights $\delta^i_1, \ldots, \delta^i_T$. $u^i_j$ is the belief degree to which $D_j$ is believed to be the consequent if in the $i$th uncertain rule the input satisfies the antecedent $A^i = \{A^i_1, \ldots, A^i_T\}$. Thus, the evidential approximate reasoning model consists of $T$ rules of the form:

$$R^i : IF S_1 is A^i_1 and \ldots and S_T is A^i_T, THEN y is m^i,$$

where $m^i$ is a BBA whose focal elements are among the hypotheses of the frame of discernment $\Omega$. Let us denote by $\mathcal{F}^i = \{F_{ij}, j = 1, J(i)\}$; the set of $J(i)$ focal elements of $m^i$ and denote by $m^i (F_{ij})$ the weight (a mass of probability) associated to the $j$th focal element $F_{ij}$ of $m^i$. This formulation which is quite general brings some aspects of the evidence theory to aggregate different BBA, where every BBA has its own focal elements. The firing strength of the $i$th rule is defined by the product of the membership degrees of the corresponding fuzzy sets:

$$\mu^i(S) = \prod_{j=1}^{T_i} \mu^i_A(j(S_j))$$

(21)

where $\mu^i_A(j(S_j))$ is the membership function of the fuzzy set $A^i_j (S_j)$. In order to diagnose the state of the system for an input vector $S$ of symptoms (also called a complex symptom), every rule provides a piece of evidence that can be assimilated by a belief function $m^i$ [12], [3]. For the purposes of the study under consideration, we take the following simplified form of the BBA:

$$\left\{ \begin{array}{ll}
m^i (\{f_i\} | S) = \phi_i (S) & \\
m^i (\Omega | S) = 1 - \phi_i (S) & \\
m^i (A | S) = 0 \forall A \in 2^\Omega - \mathcal{F}^i & \\
\end{array} \right.$$

(22)

with $2^\Omega$ is the power set of $\Omega$ and $\mathcal{F}^i$ denotes the focal elements of $m^i$. The quantities $m^i (\{f_i\} | S)$, and $m^i (A | S)$ are the masses assigned to the subsets $\{f_i\}$ and $A$ after taking knowledge of $S$. The quantity $m^i (\Omega | S)$ is the mass assigned to the frame of discernment after taking knowledge of $S$. The function $\phi_i (S)$ which is related to the input domain of the $i$th rule is defined by:

$$\phi_i (S) = \alpha_i \mu^i (S)$$

(23)

where $\mu^i (S)$ is given by (21) and $\alpha_i$ is a weighting factor which verify ($0 < \alpha_i < 1$). In order to make a decision, the outputs of the different rules which are belief structures, are combined using the Dempster’s rule of combination. The final belief structure is then:

$$m = \bigoplus_{i=1}^{K} m^i$$

(24)

where $\oplus$ represents the operator of combination and $K$ is number of rules. In the context of diagnosis, the domain of possible events $\Omega = \{f_1, f_2, \ldots, f_M, ff\}$, where $f_i$ denotes a particular faulty state, while $ff = f_{M+1}$ stands for the fault-free state. The occurrence of a complex symptom is regarded as a source of partial information providing an item of evidence in the form of a basic belief assignment $m^i$ whose focal elements depend on the elements of the incidence matrix $\Lambda = \lambda_{pq}$. An entry $\lambda_{pq} \neq 0$ means that the $q$th fault causes
the $p$th analytical symptom to become different from zero, i.e Highlight. In practical terms, this means that $|r^p| \geq h_p$ where $h_p$ is the threshold value. In [9] the transferable belief model (TBM) [10] has been used for the evaluation of residuals in a different way by considering each residual as a source of partial evidence. However, here, the diagnosis is performed by considering a combination of residuals called complex symptom.

5 Simulation studies

The simulation model is the DTS200 three-tank system which is a benchmark in process control engineering. Fig 1 shows the layout of the setup. The plant consists of three Plexiglas cylinders T1, T3 and T2 with the equivalent cross section $A$. These are connected serially with each other by cylindrical pipes with the cross section $S_n$. Located at T2 is the single so-called ”nominal outflow valve”. It has also a circular cross section $S_n$. The out flowing liquid (usually distilled water) is collected in a reservoir, which supplies the pumps 1 and 2. The pump flow rate $Q_1$ and $Q_2$ denote the input signals, which are controllable. The required level measurements are carried out by piezo-resistive differential pressure sensors and the reference pressure is the atmospheric pressure. Let us define the following variables and the parameters: $a_i$, outflow coefficients; $h_i$, liquid levels ($m$); $Q_{ij}$, flow rates ($m^3/s$); $Q_1$ and $Q_2$, supplying flow rates ($m^3/s$); $A$, section of cylinder ($m^2$); $S_n$, section of connection pipe ($m^2$); where $i = 1, 2, 3$ and $(i, j) \in \{(1, 3); (3, 2); (2, 0)\}$.

Use the balance equations to all the three cylinders, the model is setup as follows:

$$\begin{align*}
A \frac{dh_1}{dt} &= -Q_{13} + Q_1 \\
A \frac{dh_2}{dt} &= Q_{13} - Q_{32} \\
A \frac{dh_3}{dt} &= Q_{32} - Q_{20} + Q_2
\end{align*}$$

where the follows are given by generalized Torricelli-rule,

$$\begin{align*}
Q_{13} &= a_1S_n|\text{sig}(h_1 - h_3)\sqrt{2gh_1} - h_3| \\
Q_{32} &= a_3S_n|\text{sig}(h_3 - h_2)\sqrt{2gh_3} - h_2| \\
Q_{20} &= a_2S_n\sqrt{2gh_2}
\end{align*}$$

The state vector is $x = [h_1, h_3, h_2]_T^T$ and the input vector is $u = [Q_1, Q_2]_T^T$. the actual parameters are $A = 0.0154m^2, S_n = 5 \times 10^{-5}m^2, Q_{1\max} = Q_{2\max} = 100m^3/s, h_{\max} = 62 \pm 1cm, g = 1.81m/s^2, a_1 = 0.450289, a_3 = 0.461526, a_2 = 0.611429$. By using the mechanistic model it is possible to simulate different faults:

- faults in level sensors;
- faults in pump output;
- blockages in connecting pipes between tanks;
- leaks in each tank.

For example, if we take the leakage in tank 1 as a fault caused by a hole of radius $r$, then according to the generalized Torricelli-rule: $Q_{\text{leak}}^1 = a_1\pi r^2\sqrt{2gh_1}$ and the dynamics of tank 1 with fault becomes:

$$A \frac{dh_1}{dt} = -Q_{13} + Q_1 - Q_{\text{leak}}^1$$

Figure 1: The three-tank benchmark system.

5.1 Model structure

The mathematical relationships to be developed should be used to generate an enhanced set of residuals $r(t)$ so that, in response to a specific subset of the components is non-zeros. Such residual sets are called structured. The objective behind the structured analysis is to simplify the task of fault isolation and diagnosis. To this end, a deeper physical insight in the plant is required to specify some suitable relationships of the plant. Obviously, the
expert knowledge is also of great importance to determine the structure of the models, i.e. the number of fuzzy sets and the shape of the membership functions. In the present study, three basic relationships are considered:

\[ \Delta h_1 = F_1(h_{13}, Q_1), \text{ where, } h_{13} = H_1 - H_3 \]
\[ \Delta h_2 = F_2(h_{32}, Q_2, H_2), \text{ where, } h_{32} = H_3 - H_2 \]
\[ \Delta h_3 = F_3(h_{13}, h_{32}) \]

In order to obtain an additional residual, another relation has been proposed

\[ (\Delta h_1 + \Delta h_3) = F_4(h_{32}, Q_1) \]

In the identification of these relationships, the membership functions are assumed to be Gaussian with a number of five for every variable. It is important to notice that for the identification of nonlinear processes, the input signals should be rich in frequency and in amplitude in order to excite all the modes of the process [1].

5.2 Diagnostic reasoning

The effects of all faults are summarized in Table 1. Each fault leads to significant deviation in at least one feature. Therefore all faults can be detected. However, using the proposed residual set, only seven different faulty states can be isolated, see Table 2. The behaviors of the four residuals \( r_1, \ldots, r_4 \) (analytical symptoms) are shown in Fig 3-4 when abrupt faults are provoked at time \( t = 150 \) s. Fig 3 corresponds to a leak in tank 2 where the only residual \( r_2 \) has changed. Fig 4 shows the effect of a fault in pump Q1 between \( t = 100s \) and \( t = 150s \) followed by a leak in tank 3 after \( t = 200s \). The results of the evidential approximate reasoning scheme are shown in Fig 5. The evidential fuzzy rule system consists of eight rules; one for each faulty state and one for the fault free state.

6 Conclusions

This paper points out the FDD of complex systems in a systematic way using multi-model based symptom generation scheme.

### Table 1: Incident matrix.

<table>
<thead>
<tr>
<th>( r_i )</th>
<th>faults</th>
</tr>
</thead>
<tbody>
<tr>
<td>h1h2h3</td>
<td>Q1Q2</td>
</tr>
<tr>
<td>r1</td>
<td>101</td>
</tr>
<tr>
<td>r2</td>
<td>011</td>
</tr>
<tr>
<td>r3</td>
<td>111</td>
</tr>
<tr>
<td>r4</td>
<td>111</td>
</tr>
</tbody>
</table>

### Table 2: Faulty states.

\[
\begin{align*}
\bullet f_1 &= f_{Q1} \lor f_{L1} \\
\bullet f_3 &= f_{Q2} \lor f_{Qout} \lor f_{L2} \\
\bullet f_5 &= f_{h1} \\
\bullet f_7 &= f_{h3} \\
\bullet f_2 &= f_{Q13} \\
\bullet f_4 &= f_{L3} \\
\bullet f_6 &= f_{h2} \lor f_{Q32} 
\end{align*}
\]

The diagnosis procedure based on analytic process model is illustrated on the well known benchmark of the three tanks. In order to improve the quality of the diagnosis, the residual evaluation step is based on approximate reasoning scheme to produce a ranked list of possible fault candidates with different degrees of belief and a measure that indicates reliability and completeness of diagnosis. These additional features are very useful when taking a final decision.

References


[4] Frank, P. M., Fault diagnosis in dynamic systems using analytical and knowledge-
Figure 2: Example of linguistic variables of an analytic symptom $S_j$.

Figure 3: Leak in tank 2

Figure 4: Fault in pump Q1 followed by a leak in tank 3

Figure 5: The credibility functions


