PARAMETERIZATION OF A FUZZY CLASSIFIER FOR THE DIAGNOSIS OF AN INDUSTRIAL PROCESS

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Abstract

The aim of this paper is to present a classifier based on a fuzzy inference system. For this classifier, we propose a parameterization method which is not necessarily based on an iterative training. This approach can be seen as a pre-parameterization which allows the determination of the rules base and the parameters of the membership functions. We also present a continuous and derivable version of the previous classifier and suggest an iterative learning algorithm based on a gradient method. An example using the learning basis IRIS, which is a benchmark for classification problems, is presented showing the performances of this classifier. Finally this classifier is applied to the diagnosis of a D.C. motor showing the utility of this method. However in many cases the total knowledge necessary to the synthesis of the fuzzy diagnosis system is not, in general, directly available. It must be extracted from an often considerable mass of information. For this reason, a general methodology for the design of a fuzzy diagnosis system is presented and illustrated on a non-linear plant.

Key words: Diagnosis, fuzzy classification, learning, knowledge acquisition.

1 Introduction

The aim of this paper is to present a parameterization method of a fuzzy classifier from a set of examples without necessarily using a process of iterative training. A relevance criterion of the variables used for the classification is also provided. The following work is divided into three main sections. In the first section, after having presented the general structure of the diagnosis system by classification and having specified the role of the various components, we will present the global structure of the classifier and will describe its implementation in the form of Fuzzy Inferences System (FIS) with the final decision-making by thresholding.
Then we will suggest a general parameterization method of the classifier from the learning basis. We will see that this stage can be seen as a pre-parameterization of the classifier which proves to be sufficient in many cases. However, an iterative learning algorithm taking into account the discontinuity due to the thresholding is also suggested, which may allow the refinement of the pre-parameterization.

In the second section we will present two applications. The first uses the learning basis IRIS which is a benchmark for the classification problems. This will allow us to evaluate the performances of our classifier in relation to the work of other authors. The second application is dedicated to the diagnosis of a D.C. machine showing the utility of this method.

In the third section the general problem of the knowledge acquisition is examined. Obviously in many cases the total knowledge necessary for the synthesis of the fuzzy diagnosis system (FDS) is not, in general, directly available. They must be extracted from an often considerable mass of information. In the last part, a general methodology of assistance to the design of a fuzzy diagnosis system is presented. This methodology rests on the functional and dysfunctional analysis of the installation and leads to the original concept of the metamodel. Knowledge resulting from the application of this methodology can then be used to carry out the synthesis of the various components of the FDS, notably the fuzzy rules base. This new methodology is illustrated on a non-linear thermal plant.

2 General structure of the diagnosis system

The general structure of the diagnosis system is shown in figure 1: one can distinguish two levels. A system level, or level 0, whose role is mainly to generate the control law in order to ensure correct performance of the closed loop system. A supervision level, or level 1, whose role is decision making from the information generated by level 0. More precisely, the task of level 1 is fixed by a diagnosis system, consisting of an observation function $\Gamma$ of the measured variables, a classification function (pattern recognition) $\Phi$, and a decision making function $\Psi$, allowing operation on level 0 under the control of an operator.

The role of the observation function $\Gamma$ is to generate, from the measures provided by level 0, a signature written $\chi$ allowing to characterize the possible faults which might occur on the equipment. The signature generated by the observation function $\Gamma$ is then applied to the classification function $\Phi$ which will allow the recognition of the operating mode of the process. The decision making function $\Psi$ allows to act on the level 0 in relation with the operating modes recognized by the classification function. For example: the parametric adaptation of the control law in order to preserve the performances of the supervised
system, the modification of the operating point in order to meet production objectives, an emergency stop procedure if the operating mode is dangerous for the human operators or for the equipment.

![Diagram showing the general structure of the diagnosis system.](image)

**Fig. 1** - General structure of the diagnosis system.

2.1 *Synthesis of the classification function*

Figure 2 shows the global structure of the classifier. The signature written \( \mathbf{x} \) provided by the observation function is characterized by \( m \) parameters. This signature can thus be represented by the point of a space with \( m \) dimensions.

![Diagram showing the general structure of the classifier.](image)

**Fig. 2** - General structure of the classifier.

Owing to the inherent noise in the different measures, a follow-up of observations resulting from a same state of the system will not be shown on a single point but will occupy a zone of that space [2]. If the \( m \) parameters have been well chosen, a signature which corresponds to a normal operation will belong to a zone or class whereas a signature corresponding to another operation will belong to another class. The problem is thus the determination of the boundary between these zones [12].
A signature can be seen as a form which will be classified among all the forms corresponding to a normal or not normal operation. The classification is carried out with the help of the truth and decision functions, the parameterization of which establishes the boundary between the classes. The structure of the classifier will be determined on the basis of a fuzzy inference system. The learning base will first allow us to generate the rules base and then to carry out the parameterization of the membership functions.

### 2.1.1 Structure of the fuzzy classifier

The rules base of the proposed classifier (FIG. 3) is a list of fuzzy conditional statements:

$$R_i: \text{If } \left(x^1 \text{ is } \tilde{A}^i_1\right) \text{ and } \left(x^2 \text{ is } \tilde{A}^i_2\right) \text{ and } \ldots \text{ and } \left(x^n \text{ is } \tilde{A}^i_n\right) \text{ Then } x \in \zeta_i \text{ with } i = 1 \ldots r \quad (1)$$

where $r$ is the total number of rules, the $\tilde{A}^i_j$ are fuzzy sub-set (FSS) defined with the help of the membership functions written $\mu_i^j(x^i, \theta_i^j)$, and the $\zeta_i$ stand for the different classes of the classification problem. For a more detailed study consult in particular [3] and [11].

![General structure of the fuzzy classifier](image)

For this classifier, the rules base contain one and only one fuzzy rule for each class $\zeta_i$, $i = 1 \ldots r$; the membership functions $\mu_i^j(x^i, \theta_i^j)$ are assumed bell-shaped of parameters
\( \Theta' = (m', \sigma') \). This membership function represent the projection of the class \( \mathcal{C} \), which is a multidimensional fuzzy subset on the dimension \( x^j \). The truth functions \( f_i, \ i = 1 \ldots r \), are the conjunction of the rules antecedents so that \( \alpha_i \) represents the strength of the rules. The decision function is defined by the following relation:

\[
C_i = \begin{cases} 
1 & \text{if} \ (\alpha_i - \alpha_{max}) \geq 0 \\
-1 & \text{if} \ (\alpha_i - \alpha_{max}) < 0
\end{cases}
\]

where \( \alpha_{max} \) is the maximum of the strength of the rules, thus, the input belong to the class for which \( C_i = 1 \).

The structure of the classifier being fixed, the only adjustable elements are the parameters \( \Theta' \) of the membership functions. The object of the following paragraph is precisely to define the network structure as well as the parameterization of the membership functions.

### 2.1.2 Parameterization of the fuzzy classifier

The parameterization of the classifier is similar to that of the neuro-fuzzy networks [8]. This parameterization consists of two distinct parts: the structural adjustment and the parametric adjustment. The structural adjustment consists in establishing the classifier structure, that is to say the number of inputs, the number of outputs and the rules base. The parametric adjustment consists in determining the values of the parameters which affect the membership functions. The parametric adjustment can thus be carried out with the help of a learning from examples. The training of the classifier can be broken down into three distinct phases: the creation of a learning base (or file), the network training and, at last, a test phase allowing the validation of the network. The learning file is a set of signatures for which the class is known. The training phase is the procedure of the parameters calculation so that for each given input, the desired response is obtained on the output. The classifier is then fixed and will not be modified again. We will now suggest a method for the automatic generation of the rules base as well as the parameterization of the membership functions. Let us consider first of all the pre-parameterization of the classifier.

Let \( E \) be the training set \( E = \{(x(k), C_d(k)), k = 1, \ldots, N\} \), where \( N \) is the total number of signatures with:

\[
\begin{align*}
\begin{bmatrix} x(k) = \left[ x^1(k) & x^2(k) & \cdots & x^n(k) \right]^T \\
C_d(k) = \begin{bmatrix} C_1^d(k) & C_2^d(k) & \cdots & C_r^d(k) \end{bmatrix}
\end{bmatrix}
\end{align*}
\]
where $x(k)$ is the $k^{th}$ signature, and $C_d(k)$ the corresponding output vector. We gather in $\mathbf{X}_i$, the set of vectors of the learning base belonging to the class $C_i$:

$$\mathbf{X}_i = \left\{ x(k) / x(k) \in C_i \right\}; \quad \mathbf{X}_i \subset C_i$$

$$\text{Card}(\mathbf{X}_i) = k_i; \quad \sum_i k_i = N \quad (3)$$

For each of these sub-sets, we can then define the parameters : average and standard deviation of each of the input variables :

$$m_i^j = \frac{1}{k_i} \sum_{k=1}^{k_i} x_i^j(k), \quad \sigma_i^j = \sqrt{\frac{1}{k_i} \sum_{k=1}^{k_i} \left(x_i^j(k) - m_i^j\right)^2} \quad (4)$$

where $m_i^j$ is center of the class $i$ projected on the dimension $x^j$; $\sigma_i^j$ is the domain of the class $i$ projected on the dimension $x^j$.

The relevance of the variables used for the classification can be evaluated by the following relations:

$$m^j = \frac{1}{r} \sum_{i=1}^{r} m_i^j, \quad \sigma^j = \sqrt{\frac{1}{r} \sum_{i=1}^{r} (m_i^j - m^j)^2} \quad (5)$$

$\sigma^j$ can be seen as a measure of the separability of the class for the input variable $x^j$. It is not easy to determine the value of $\sigma^j$ for which the considered variable is relevant for the classification, but that is however a useful indication for selecting the variables most useful for the classification. If, for example, among 10 variables available for classification, it is necessary to select 5 of them, one will retain only the 5 variables having the largest $\sigma^j$.

We will now propose an iterative training algorithm using the approach shown above as an initialisation. The application of this algorithm requires a continuous derivable version of the fuzzy classifier, for this reason the decision function must be built with continuous operators. In figure 4, we show the structure which will be used later, the thresholding is here carried out with the help of a tangent hyperbolic of parameter $\beta$ (which is a continuous function): $th(\beta, \zeta_i(k)) = (1 - e^{-\beta \zeta_i(k)})/(1 + e^{-\beta \zeta_i(k)})$. The max operator is here the sum-product which is, just like max, a fuzzy disjonction operator [3]. The output number $i$ of the network for the input signature $x(k)$ is given by:

$$\begin{cases}
C_i(k) = th(\beta, \zeta_i(k)); \quad \zeta_i(k) = \alpha_i(k) - \alpha_{\text{max}}(k) \\
\alpha_{\text{max}}(k) = \sum_{i=1}^{r} \alpha_i(k) - \prod_{i=1}^{r} \alpha_i(k); \quad \alpha_i(k) = \prod_{j=1}^{m} \mu_j^i(x^j, \theta_j) \quad i = 1 \ldots r
\end{cases} \quad (6)$$
where $\alpha_i$ represents the strength of the rules, $\alpha_{\text{max}}$ the output of the sum-product operator and $C_i$ the output of the continuous decision function.

**Decision function :** $d(\mathbf{x})$

$$
\begin{align*}
C_1 &= \frac{1 - e^{-\beta_1}}{1 + e^{-\beta_1}} \\
C_2 &= \frac{1 - e^{-\beta_2}}{1 + e^{-\beta_2}} \\
C_r &= \frac{1 - e^{-\beta_r}}{1 + e^{-\beta_r}}
\end{align*}
$$

**Truth function:** $f(\mathbf{x}, \mathbf{q})$

$$
\begin{align*}
f_1(x, q_1) &= \mu_1^1(x, \theta_1^1) \\
f_2(x, q_2) &= \mu_2^2(x, \theta_2^2) \\
f_r(x, q_r) &= \mu_r^r(x, \theta_r^r)
\end{align*}
$$

**Fig. 4 -** The continuous derivable fuzzy classifier.

The parameters are adjusted in order to minimize the quadratic average of estimation error calculated on $n$ examples:

$$
\begin{align*}
J_i^n(\theta_i) &= \frac{1}{n} \sum_{k=1}^{n} \varepsilon_i^2(k) = \frac{1}{n} \sum_{k=1}^{n} (C_i^d(k) - C_i(k))^2 \\
1 \leq n \leq N
\end{align*}
$$

This criterion can be minimized with the help of a gradient method. The parameters are then updated with the help of the following equations:

$$
\begin{align*}
\Delta m_i^j &= -\lambda \frac{\partial J_i^n}{\partial m_i^j} \\
\Delta \sigma_i^j &= -\lambda \frac{\partial J_i^n}{\partial \sigma_i^j}
\end{align*}
$$

where $\lambda$ is the learning coefficient. The training procedure is iterated until the criterion is inferior to the desired accuracy threshold.
3 Results

In this section we present the results obtained from a classification problem. The data base used is the set of Iris data (FIG. 5) which is a benchmark for classification problems.

![Graphs showing projections of Iris data in different planes](image1.png)

**FIG. 5.** The IRIS data base.
This data base contains 150 signatures belonging to three different classes: $\mathcal{C}_1$ (Iris-Setosa), $\mathcal{C}_2$ (Iris-Versicolor), $\mathcal{C}_3$ (Iris-Virginica), that is to say 50 signatures per class. Each signature is made up of four parameters: the height and length of the sepals and of the Iris petals. For the training base we use 25 signatures per class. The other 25 are used as a test file. The application of the method presented leads to the following rules base:

\[
\begin{align*}
\text{If } (x^1 \text{ is } \tilde{A}_1^1) \text{ and } (x^2 \text{ is } \tilde{A}_1^2) \text{ and } (x^3 \text{ is } \tilde{A}_1^3) \text{ and } (x^4 \text{ is } \tilde{A}_1^4) \text{ Then } & x \in \mathcal{C}_1 \\
\text{If } (x^1 \text{ is } \tilde{A}_2^1) \text{ and } (x^2 \text{ is } \tilde{A}_2^2) \text{ and } (x^3 \text{ is } \tilde{A}_2^3) \text{ and } (x^4 \text{ is } \tilde{A}_2^4) \text{ Then } & x \in \mathcal{C}_2 \\
\text{If } (x^1 \text{ is } \tilde{A}_3^1) \text{ and } (x^2 \text{ is } \tilde{A}_3^2) \text{ and } (x^3 \text{ is } \tilde{A}_3^3) \text{ and } (x^4 \text{ is } \tilde{A}_3^4) \text{ Then } & x \in \mathcal{C}_3
\end{align*}
\]  

(9)

FIG. 6 - Membership functions of the variables $x^1, x^2, x^3, x^4$.  

The membership functions obtained are presented in figure 6. With this classifier we obtain a success rate of 97%, which is better than the results obtained in [4] for the same cardinality of partitions and for a different classifier (neural network, fuzzy network). We achieve a result similar to those obtained by Nauck and Kruse [11], [12] which uses a base of 7 rules.
The second application concerns the diagnosis of a direct-current (DC) machine. Figure 7 reminds the structure of a DC machine with permanent magnets.

\[
E = k \omega
\]

**Fig. 7** - D.C. motor.

<table>
<thead>
<tr>
<th></th>
<th>Fault of the speed sensor</th>
<th>Fault of the current sensor</th>
<th>Fault of the power interface</th>
</tr>
</thead>
<tbody>
<tr>
<td>( r_\omega ) (V)</td>
<td>1.0</td>
<td>0.0</td>
<td>0.5</td>
</tr>
<tr>
<td>( r_i ) (V)</td>
<td></td>
<td>-1.0</td>
<td>-1.0</td>
</tr>
<tr>
<td>( r_{\text{lim}} ) (V)</td>
<td></td>
<td>0.1</td>
<td>10</td>
</tr>
<tr>
<td>( r_u ) (V)</td>
<td></td>
<td>0.01</td>
<td>-0.5</td>
</tr>
</tbody>
</table>

**Fig. 8** - Residuals table.
The current control of this device is carried out with the help of a proportional and integral action compensator. We wish to carry out the detection and localization of the following faults: \( f_w \) (fault of the speed sensor), \( f_i \) (fault of the current sensor) and \( f_{alim} \) (fault of the power interface). Conforming to the structure of figure 1, the observation function is here carried out with the help of a residual generator. This residual generator is made with the help of a Luenberger observer allowing the estimation of the measured variables. The residuals are then generated with the help of the deviations between the measured outputs and the estimated outputs. \( r_w \) is the residual of the speed sensor, \( r_i \) the residual of the current sensor, \( r_{alim} \) the residual of the power interface and \( r_u \) the residual of the PI compensator. Figure 8 shows the residuals obtained for various faults. The observation of this residuals table for the different faults to detect, leads us to adopt the following rules base for the fuzzy classifier:

\[
\begin{align*}
\text{If } & (r_w \text{ is } \tilde{Z}_w) \text{ and } (r_i \text{ is } \tilde{Z}_i) \text{ and } (r_{alim} \text{ is } \tilde{Z}_{alim}) \text{ and } (r_u \text{ is } \tilde{Z}_u) \text{ then } r \in \mathcal{C}_1, \\
\text{If } & (r_w \text{ is } \tilde{Z}_w) \text{ and } (r_i \text{ is } \tilde{Z}_i) \text{ and } (r_{alim} \text{ is } \tilde{Z}_{alim}) \text{ et } (r_u \text{ is } \tilde{Z}_u) \text{ then } r \in \mathcal{C}_2, \\
\text{If } & (r_w \text{ is } \tilde{Z}_w) \text{ and } (r_i \text{ is } \tilde{Z}_i) \text{ and } (r_{alim} \text{ is } \tilde{Z}_{alim}) \text{ and } (r_u \text{ is } \tilde{Z}_u) \text{ then } r \in \mathcal{C}_3, \\
\text{If } & (r_w \text{ is } \tilde{Z}_w) \text{ and } (r_i \text{ est } \tilde{Z}_i) \text{ and } (r_{alim} \text{ is } \tilde{Z}_{alim}) \text{ and } (r_u \text{ is } \tilde{Z}_u) \text{ then } r \in \mathcal{C}_4.
\end{align*}
\]

where \( \mathcal{C}_1 \) is the class corresponding to a normal operation, \( \mathcal{C}_2 \) the class corresponding to a defect on the speed sensor, \( \mathcal{C}_3 \) the class corresponding to a defect on the current sensor and \( \mathcal{C}_4 \) the class corresponding to a defect of power interface. In this rules base, the fuzzy subsets \( \tilde{Z}_w, \tilde{Z}_i, \tilde{Z}_{alim}, \tilde{Z}_u \) are the same for all rules.

**FIG. 9** - Membership functions of the variables \( r_w, r_i, r_{alim}, r_u \).
The application of the method presented enables us to parametrize the membership functions of the FSS associated with the residuals, $r_w$, $r_i$, $r_{lim}$ and $r_u$. The membership functions obtained are presented in figure 9. Note that « no $\tilde{Z}$ » is the negation of $\tilde{Z}$, the membership function of the fuzzy-subset « no $\tilde{Z}$ » is then computed by $1 - \mu_{\tilde{Z}}$, where $\mu_{\tilde{Z}}$ is the membership function of $\tilde{Z}$. Figure 10 show the behavior of the fuzzy classifier when a fault of the speed sensor occur at time 10s. For time in the interval 0 to 10s, the outputs are: $C_1 = 1$ and $C_2 = C_3 = C_4 = -1$, this imply no fault. From time 10s, we have $C_1 = C_3 = C_4 = -1$ and $C_2 = 1$, that is fault of the speed sensor (for the clarity of the figure, the outputs C3 and C4 are not presented).

![Figure 10 - Abrupt fault of the speed sensor](image)

Fig. 10 -. Abrupt fault of the speed sensor.

The fuzzy classifier thus defined allows the detection and the localization of the faults: current sensor, speed sensor and the power interface.

4 The problem of the knowledge acquisition

In the previous example, the whole knowledge is available for the synthesis of a diagnosis system, however in many practical problems this is not always the case. All diagnosis methods assume the existence of particular knowledge. For example the precise mathematical model of the system, the existence of a numerical data base corresponding to the various operating modes of the installation [1], [7], [13], [6], or even the existence of experts able to verbalize their experience of a given process etc. In fact this is not true in many industrial systems, for example, it is very rare to have a precise mathematical model of the whole process.
In general the total knowledge for the synthesis of a diagnosis system must be extracted from an often considerable mass of information. It is then necessary to adopt an efficient method in order to obtain this knowledge. Of course, the work presented in the next paragraphs does not claim to provide a complete solution to this difficult problem. We propose however a methodology, undoubtedly perfectible, allowing an assistance for the designer in charge of a diagnosis system synthesis.

4.1 Principle of the method

The objective is to ensure a reliable operation of the installation, it is then necessary to take into account the whole of the failures which affect the safety and the availability of the studied system. This can be obtained by a dysfunctional analysis of the installation. However this dysfunctional analysis requires the whole functions ensured by the considered system. The dysfunctional analysis must be thus preceded by a functional analysis. In addition, this functional analysis will make it possible to carry out a functional diagram. This functional diagram will be extremely useful for obtaining a total model of the process. The term of model must be understood here in a very large sense. It does not mean the exclusive use of mathematical equations, for this reason we will use hereafter the term metamodel. This metamodel allows many knowledge type of the process : analytical, numerical, symbolic etc.

Finally after the analysis stage, we thus have a metamodel \( M \), a list of the defects \( F \) to be detected and locate and a list of the actions \( A \) to be undertaken for each defect. These three elements will be used to carry out the synthesis of a diagnosis system. Figure 11 presents in a very brief way, the principle of this methodology.

![Diagram](image)

FIG. 11 -. Principle of the method.

4.2 Example of application

One consider in this example a non linear thermal device, whose schematic diagram is given figure 12.
This installation is made up of a plexiglass cylinder, a ventilator making it possible to insufflate the ambient air inside the tube and heating resistances. The ambient air is introduced into the tube with an adjustable flow \( q_e \) by the control variable \( u_v \). An electric heating system makes it possible to increase the temperature of the air flow by modulation of the current in the resistances by the control \( u_c \). A commutation device, under the action of the control \( u_{sp} \), modifies the pace of heating by modification of the resistances coupling (serial or parallel). The goal of this installation (total objective) is to provide a flow of hot air with a flow and an adjustable temperature.

### 4.2.1 Development of the metamodel

All the installation is designed to carry out a well defined total objective. The functional analysis makes it possible to break up this total objective into functions and sub-functions. In the case of the installation considered here, the main functions are: \( F_{p1} = "create an air flow " \) and \( F_{p2} = "heat air flow " \). The originality of our approach as follows: for all low levels of the decomposition a functional diagram is associated revealing the technical solution used for the realization of the function as well as the concerned physical variables (FIG. 13).
This mode of analysis allows an easy passage to the functional diagram of the total installation (FIG. 14).

Fig. 14 -. Functional diagram of the total system.

The following stage for obtaining the metamodel will be to provide an explanatory model of each block of the functional diagram. The study of technical documentation relating to each block of the installation leads to the metamodel shown in figure 15.

Fig. 15 -. Metamodel of the installation.
4.2.2 Dysfunctional analysis of the installation

This stage can be carried out using an analysis making it possible to identify in a systematic way the risks of abnormal operation and the origins and their consequences. It makes it possible to show the critical points and to propose adapted corrective actions. The dysfunctional analysis of this installation (not reproduced here) shows that the reliability of this installation requires fault detection of the following elements: card of commutation, power interfaces, block ventilator and heat resistors.

4.2.3 Analysis of the symptoms associated with the faults

The metamodel of the installation is defined by the following relations of causality:

\[
\begin{bmatrix}
\text{Com1}(t) \\
\text{Com2}(t)
\end{bmatrix} = \text{Op}_1\left(u_{sp}(t)\right)
\]
\[
u_{sp}(t) = \text{Op}_2\left(u_c(t)\right)
\]
\[
q_c(t) = \text{Op}_3\left(u_c(t)\right)
\]
\[
p_{ch}(t) = \text{Op}_4\left(\text{Com1}(t), \text{Com2}(t), u_{sp}(t)\right)
\]
\[
\begin{bmatrix}
q_s(t) \\
\theta_s(t)
\end{bmatrix} = \text{Op}_5\left(q_c(t), q_s(t), p_{ch}(t)\right)
\]

(10)

where \(\text{Op}_1,\ldots,\text{Op}_5\) are defined figure 15, \(u_{sp}\) is the control variable of the commutation card and \(\text{Com1, Com2}\) the outputs, \(u_c\) is the control variable of the power alimentation \(u_{sp}\), \(u_c\) is the control variable of the input air flow \(q_c\), \(p_{ch}\) is the heat power, \(\theta_e\) the external temperature, \(q_s\) the output air flow and \(\theta_s\) the output air temperature.

These relations are used to build table 1 (see below), showing the effect of the fault affecting one of the blocks operation \(\text{Op}_1,\ldots,\text{Op}_5\) on the various variables of the system.

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<tbody>
<tr>
<td>(C₁)</td>
<td>(\times)</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>(C₂)</td>
<td>(\times)</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>(u_{sp})</td>
<td>-</td>
<td>(\times)</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>(q_c)</td>
<td>-</td>
<td>-</td>
<td>(\times)</td>
<td>-</td>
</tr>
<tr>
<td>(p_{ch})</td>
<td>(\times)</td>
<td>(\times)</td>
<td>-</td>
<td>(\times)</td>
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<tr>
<td>(q_s)</td>
<td>(\times)</td>
<td>(\times)</td>
<td>(\times)</td>
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<tr>
<td>(\theta_s)</td>
<td>(\times)</td>
<td>(\times)</td>
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</table>

**TABLE 1** - Effect of the faults on the variables of the system.
According to the dysfunctional analysis, it is necessary to detect the faults on the blocks $Op_1$ (Card of commutation), $Op_2$ (Power interface), $Op_3$ (Block ventilator), $Op_4$ (Heat resistors). The fault detection on the block $Op_5$ is useless because it necessarily results from a defect on the other blocks.

The problem is a correct choice of the variables to be measured in order to detect and determine the fault components. Analysis of the table 1 leads to the measure of the variables $C_1$, $u_{eff}$, $P_{ch}$ and $q_s$. These measures make it possible to detect and localize of the faults, this is shown in table 2.

<table>
<thead>
<tr>
<th></th>
<th>Fault $Op_1$</th>
<th>Fault $Op_2$</th>
<th>Fault $Op_3$</th>
<th>Fault $Op_4$</th>
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<tbody>
<tr>
<td>$C_i$, ($r_1$)</td>
<td>×</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>$u_{eff}$, ($r_2$)</td>
<td>-</td>
<td>×</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>$P_{ch}$, ($r_3$)</td>
<td>×</td>
<td>×</td>
<td>-</td>
<td>×</td>
</tr>
<tr>
<td>$q_s$, ($r_4$)</td>
<td>×</td>
<td>×</td>
<td>×</td>
<td>×</td>
</tr>
</tbody>
</table>

TABLE 2 - Effect of the faults on the measured variables.

where $r_i$ ($i=1,...,4$) is the difference between the normal value of the variable for a given operating point and the corresponding measured value. This table can be used for the determination of the fuzzy rules base. The fuzzy rules base obtained from this table is the following:

$$\begin{align*}
\text{If } (r_1 \text{ is } \tilde{Z}_1) \text{ and } (r_2 \text{ is } \tilde{Z}_2) \text{ and } (r_3 \text{ is } \tilde{Z}_3) \text{ and } (r_4 \text{ is } \tilde{Z}_4) \text{ then } \tau \in \mathcal{C}_0 \\
\text{If } (r_1 \text{ is no } \tilde{Z}_1) \text{ and } (r_2 \text{ is } \tilde{Z}_2) \text{ and } (r_3 \text{ is no } \tilde{Z}_3) \text{ and } (r_4 \text{ is no } \tilde{Z}_4) \text{ then } \tau \in \mathcal{C}_1 \\
\text{If } (r_1 \text{ is } \tilde{Z}_1) \text{ and } (r_2 \text{ is no } \tilde{Z}_2) \text{ and } (r_3 \text{ is no } \tilde{Z}_3) \text{ and } (r_4 \text{ is no } \tilde{Z}_4) \text{ then } \tau \in \mathcal{C}_2 \\
\text{If } (r_1 \text{ is } \tilde{Z}_1) \text{ and } (r_2 \text{ is } \tilde{Z}_2) \text{ and } (r_3 \text{ is } \tilde{Z}_3) \text{ and } (r_4 \text{ is } \text{ no } \tilde{Z}_4) \text{ then } \tau \in \mathcal{C}_3 \\
\text{If } (r_1 \text{ is } \tilde{Z}_1) \text{ and } (r_2 \text{ is } \tilde{Z}_2) \text{ and } (r_3 \text{ is } \text{ no } \tilde{Z}_3) \text{ and } (r_4 \text{ is } \text{ no } \tilde{Z}_4) \text{ then } \tau \in \mathcal{C}_4
\end{align*}$$

where the fuzzy subsets $\tilde{Z}_1, \tilde{Z}_2, \tilde{Z}_3, \tilde{Z}_4$ are the same for all rules. This rules base can then be used for the fuzzy diagnosis system with the classifier presented in the first part.

5 Conclusion

In this paper, we have presented a general methodology allowing the structural and parametric parameterization of a classifier. The suggested classifier is directly derived from a fuzzy inferences system. The learning base necessary for classification problems, enables us to generate the rules base as well as the initial parameterization of the membership functions.
An iterative training algorithm allows the eventual refinement of the parameterization thus carried out. The effectiveness of this approach is presented on a benchmark classification problem with the IRIS data base. An example of diagnosis of a D.C. machine was presented showing the utility of the method for the monitoring of industrial devices.

We have also examined the problem of the knowledge acquisition, in this way a general methodology of assistance to the design of a diagnosis system is presented. The approach suggested makes it possible to extract from the rough data relating to the installation, all information useful for the synthesis of a diagnosis system. We have, for this purpose, introduced the concept of metamodel which is a more or less fine representation of the behavior of the system. This representation makes it possible to include an explanatory model of the operation of the various elements of the installation that it is: analytical, numerical, symbolic system etc. The development of the metamodel rests on a functional analysis of the process followed by a detailed study of its technical documentation.

The proposed approach makes it possible to determine the fuzzy rules base assuring with the fuzzy classifier the detection and the localization of the faults system.

References


