Decentralized Approach for Fault Diagnosis of Three Cell Converters

Hanane Louajri, Moamar Sayed-Mouchaweh

Université Lille Nord de France, Mines-Douai, IA 941, rue Charles Bourseul 59508 Douai, France
(e-mail: [hanane.louajri, moamar.sayed-mouchaweh]@ mines-douai.fr).

ABSTRACT

In this paper, an approach for fault diagnosis of hybrid dynamic systems (HDS), in particular discretely controlled continuous system, is proposed. The goal is to construct a decentralized diagnosis structure, able to diagnose parametric and discrete faults. This approach considers the system as composed of a set of interacted hybrid components (HCs). Each HC is composed of a discrete component (Dc), e.g. on/off switches, with the continuous components (Cc), e.g. capacitors, whose continuous dynamic behavior is influenced by the Dc discrete states. A local hybrid diagnosis module, called diagnoser, is associated to each HC in order to diagnose the faults occurring in this HC. In order to take into account the interactions between the different HCs, local diagnosis decisions are merged using a coordinator. The latter issues a final decision about the origin of the fault and identifies its parameters. The advantage of the proposed approach is that local hybrid diagnosers as well as the coordinator are built using local models. The proposed approach is applied to achieve the decentralized diagnosis of discrete and parametric faults of power electronic three-cell converters.

1. INTRODUCTION

1.1 Basic definitions and motivation

A fault can be defined as a non-permitted deviation of at least one characteristic property of a system or one of its components from its normal or intended behavior. Fault diagnosis is the operation of detecting faults and determining possible candidates that explain their occurrence. Most of real systems are hybrid dynamic systems (HDS) (Zaytoon, 2001), (Arogeti et al., 2010) in which the discrete and continuous dynamics cohabit. Therefore, fault diagnosis of HDS must deal with the evolution of continuous dynamics in each discrete mode in order to construct a diagnosis module (called diagnoser) able to diagnose parametric and discrete faults. Parametric faults affect the system continuous dynamics and are characterized by abnormal changes in some system parameters; whereas discrete faults affect the system discrete dynamics and are considered either as the occurrence of unobservable events and/or reaching discrete fault modes. In both cases, they entail unpredicted, abnormal, change in the system configuration. Therefore faults may be modelled in HDS by introducing parameters into the system model, explicit fault events or/and fault modes.

Discretely controlled continuous systems (DCCS) (Schild and Lunze, 2008) are a special class of HDS widely used in the literature. In these systems, the changes in discrete modes are achieved by discrete control commands, e.g. opening or closing a switch.

1.2 State of the art

Many approaches have been proposed in the literature for fault diagnosis of DCCS. They are generally divided into three main categories:

- approaches for the diagnosis of parametric faults,
- approaches for the diagnosis of discrete faults,
- approaches for the diagnosis of both parametric and discrete faults.

In parametric fault diagnosis approaches, (Cocquempot et al., 2004), (Alavi et al., 2011), (Kamel et al., 2012) relations over observable variables are computed in order to generate residuals sensitive to a certain subset of parametric faults in each observable discrete mode.

The discrete fault diagnosis approaches are divided into three main groups. In the first group (Rahimnejad et al., 2012), (Defoort et al., 2011), residuals sensitive to the continuous dynamics in each discrete mode are defined. If unpredicted change occurs due to the occurrence of unobservable discrete fault, the residuals, defined for the
discrete mode before the fault occurrence, will be different of zero in the discrete mode after the fault occurrence. This change of residuals values from zero indicates the occurrence of a discrete fault. The approaches of second group (Bhowal et al., 2007), (Biswas et al., 2006), describe in each normal or fault discrete mode, continuous dynamics as the rate of changes of continuous variables. These rates are considered to be constant. Transition guards are defined as linear inequalities based on continuous variables values. When a guard is satisfied, its corresponding mode transition is enabled. The occurrence of a fault is diagnosed by determining the discrete state reached due to specific guard satisfaction. In the methods of last group (Bayoudh et al., 2006), a set of residuals is defined in each normal or fault discrete mode. Each residual is characterized by three symbols: 0, 1 or und when the residual value is, respectively, zero, different of zero and undefined. und represents the case where the associated residual is not defined in the new active mode. These symbols are used to distinguish the different normal and fault discrete modes. A discrete fault is isolated by determining the current discrete fault mode of the system.

The third category includes few approaches for the diagnosis of both parametric and discrete faults. Some approaches of this category (Derbel et al., 2009), capture the continuous dynamics by integrating the occurrence time of events. They consider that the occurrence of discrete or parametric faults does not change events ordering but only alters their timing characteristics. Therefore, a discrete or parametric fault is diagnosed when predicted events occur too late or too early or they do not occur at all during their predefined time intervals. Other methods (Daigle et al., 2010), construct temporal causal graphs (TCG) for each normal and fault discrete mode based on the use of a global hybrid bond graph. When measurement deviations, caused by fault occurrence, are observed through residuals, TCG are used to determine the effects that faults will have on the measurements as well as the temporal order in which they deviate. Then, fault signature is defined for each fault as the qualitative value of the magnitude and the first non-zero derivative change which can be observed in the residuals. In order to distinguish parametric from discrete faults, the signatures are extended by adding discrete symbols indicating abrupt changes from zero to non-zero or from non-zero to zero. In (Louajri et al., 2013), an approach based on a diagnoser with hybrid structure is developed. It consists of three parts: the discrete diagnoser, the continuous diagnoser and the coordinator. The discrete diagnoser is built using a discrete time hybrid automata representing global model. It exploits the information extracted from the system continuous dynamics to get rid of diagnosis ambiguity due to the system behavior abstraction. The continuous diagnoser generates residuals. The latter compare the measured and nominal values of each continuous variable in order to diagnose the parametric faults in each discrete mode. The information about the discrete mode is provided to the continuous diagnoser thanks to the information extracted from the discrete dynamics. Finally, the coordinator uses the decisions issued from the discrete and continuous diagnosers in order to diagnose faults requiring the interaction between both diagnosers.

1.3 Our approach

Fault diagnosis approaches of the literature do not scale to HDS with a large number of discrete modes because they achieve fault diagnosis using one centralized diagnosis module. The latter is built using a global model of the system. Two problems are arisen - the weak robustness in the sense that, when the global diagnosis module fails, this may bring down the entire diagnosis task and - the system global model can be too huge to be physically constructed. Therefore in this paper, the proposed approach of (Louajri et al., 2013) is developed to achieve the diagnosis of parametric and discrete faults in decentralized manner using several local hybrid diagnosers. The latter are constructed without the use of a global model of the system but only the local models of the system discrete components (Figure 1).

The paper is organized as follows. In section 2, the three cell converter system is described and modelled. Section 3 defines the steps of the hybrid diagnosis construction. In section 4, a simulation for the three-cell converter is used to demonstrate the efficacy of the approach. A conclusion with the future work ends the paper in section 5.

![Decentralized hybrid diagnosis structure for a HDS composed of 3 interacted HCs.](image)

**Figure 1.** Decentralized hybrid diagnosis structure for a HDS composed of 3 interacted HCs.

### 2. THREE CELL CONVERTER DESCRIPTION AND MODELING

#### 2.1. System description

In order to illustrate the proposed approach, the decentralized fault diagnosis of three-cell converters...
The continuous dynamics of the system are described by state vector \( X = [V_{C1} V_{C2} I]^T \), where \( V_{C1} \) and \( V_{C2} \) represent, respectively, the floating voltage of capacitors \( C_1 \) and \( C_2 \) and \( I \) represents the current flowing from source \( E \) towards load \( (R,L) \) through three elementary switching cells \( S_j, j \in \{1,2,3\} \). The latter represent the system discrete dynamics. Each discrete switch \( S_j \) has two discrete states: \( S_j \) opened \( (h^j_q = 0) \) or \( S_j \) closed \( (h^j_q = 1) \), where \( h^j_q \) is the state discrete output of \( S_j \). The control of this system has two main tasks: - balancing the voltages between the switches and - regulating the load current to a desired value. To accomplish that, the controller changes the switches’ states from opened to closed or from closed to opened by applying discrete commands ‘close’ or ‘open’ to each discrete switch \( S_j, j \in \{1,2,3\} \) (see Fig.2). Thus, the considered example is a DCCS.

\[
\begin{align*}
V_{C1} &= -h^1_q \frac{1}{C_1} I + h^2_q \frac{1}{C_1} L \\
V_{C2} &= -h^2_q \frac{1}{C_2} I + h^3_q \frac{1}{C_2} L \\
I &= -\frac{L}{C_1} V_{C1} + \frac{L}{C_2} (V_{C2} - V_{C1}) + \frac{1}{C_2} (E - V_{C2})
\end{align*}
\]

As shown in (1), the discrete state of \( S_1 \), represented by a real discrete output \( h^1_q \), influences the dynamic evolution of \( V_{C1} \) and \( I \). The discrete state of \( S_2 \), represented by \( h^2_q \), impacts the dynamic evolution of \( V_{C1} \), \( V_{C2} \) and \( I \). The discrete state of \( S_3 \), represented by \( h^3_q \), influences the dynamic evolution of \( V_{C1} \) and \( V_{C2} \). Thus, the three-cell converter system is decomposed into three interacted HCIs as shown in Fig.2:

- \( HC_1 \) is composed of switch \( S_1 (D_{C1}), V_{C1} (C_{C1}) \) and \( I (C_{C1}) \).
- \( HC_2 \) is composed of switch \( S_2 (D_{C2}), V_{C1} (C_{C1}), V_{C2} (C_{C2}) \) and \( I (C_{C3}) \).
- \( HC_3 \) is composed of switch \( S_3 (D_{C3}), V_{C2} (C_{C2}) \) and \( I (C_{C3}) \).

In the literature (Defoort et al., 2011), (Uzunova et al., 2012), eight faults are considered for the diagnosis of the three-cell converters system (Table 1).

<table>
<thead>
<tr>
<th>Fault type</th>
<th>Fault labels</th>
<th>Fault description</th>
</tr>
</thead>
<tbody>
<tr>
<td>Discrete faults</td>
<td>F1</td>
<td>( S_1 ) stuck opened</td>
</tr>
<tr>
<td></td>
<td>F2</td>
<td>( S_2 ) stuck opened</td>
</tr>
<tr>
<td></td>
<td>F3</td>
<td>( S_2 ) stuck closed</td>
</tr>
<tr>
<td></td>
<td>F4</td>
<td>( S_3 ) stuck opened</td>
</tr>
<tr>
<td></td>
<td>F5</td>
<td>( S_3 ) stuck closed</td>
</tr>
<tr>
<td>Parametric faults</td>
<td>F6</td>
<td>Change in the nominal parameter values of ( C_1 ) due to ( C_1 ) ageing</td>
</tr>
<tr>
<td></td>
<td>F7</td>
<td>Change in the nominal parameter values of ( C_2 ) due to ( C_2 ) ageing</td>
</tr>
</tbody>
</table>

Labels \( N_1, N_2 \) and \( N_3 \) signify the normal operating modes for, respectively, \( HC_1, HC_2 \) and \( HC_3 \).

### 2.3 Residuals generation

In order to show the influence of each discrete component on the dynamic evolution of each continuous component, (1) is rewritten as follows:

\[
\begin{align*}
V_{C1} &= \dot{V}_{C1} + \dot{V}_{C2} \\
\dot{V}_{C2} &= \dot{V}_{C2} + \dot{V}_{C3} \\
\dot{I} &= \dot{I} + \dot{I} + \dot{I}^3
\end{align*}
\]

where \( \dot{V}_{C1} = -h^1_q \frac{1}{C_1} I - \frac{h^1_q}{C_1} I \), \( \dot{V}_{C2} = \frac{h^2_q}{C_1} I \), \( \dot{V}_{C2} = -h^2_q \frac{1}{C_2} I \), \( \dot{V}_{C3} = h^3_q \frac{1}{C_2} I \), \( \dot{I} = \frac{h^1_q}{C_2} V_{C1} \), \( \dot{I} = \frac{h^2_q}{C_2} \), \( \dot{I} = \frac{h^3_q}{C_2} (V_{C2} - V_{C1}) \), \( \dot{I}^3 = \frac{h^3_q}{C_2} (E - V_{C2}) \).

\( V_{C1} \) represents the real dynamic evolution of \( V_{C1} \) according to the discrete state of \( S_1 (D_{C1}) \). Likewise, \( \dot{V}_{C1} \), \( \dot{V}_{C2} \), \( \dot{V}_{C3} \), \( \dot{I} \), \( \dot{I} \) and \( \dot{I}^3 \) have the same definition as \( V_{C1} \). \( \dot{I} \) represents the part of dynamic evolution of \( I \) which does not depend on the discrete state of any switch.

Similarly, considering that the parametric faults related to the load \((R,L)\) are not considered, the equations system for the nominal dynamic evolution of system components can be written as:
\[
\begin{align*}
\tilde{V}_{c_1} &= \tilde{V}_{c_1}^1 + \tilde{V}_{c_1}^2 \\
\tilde{V}_{c_2} &= \tilde{V}_{c_2}^3 \\
\tilde{I} &= \tilde{I}_c + \tilde{I}_d + \tilde{I}_3
\end{align*}
\]

\[
\tilde{V}_{c_1}^1 = -\tilde{h}_c^1 \tilde{I}, \quad \tilde{V}_{c_2}^3 = \tilde{h}_c^3 \tilde{I}, \quad \tilde{V}_{c_2}^2 = -\tilde{h}_c^2 \tilde{I}, \quad \tilde{V}_{c_3}^3 = \tilde{h}_c^3 \tilde{I}_c + \tilde{I}_c = -\frac{R}{L} \tilde{I}, \quad \tilde{I}_d = \tilde{h}_c^1 \tilde{V}_{c_1}, \quad \tilde{I}_3 = \tilde{h}_c^3 \tilde{V}_{c_2} - \tilde{V}_{c_1}, \quad \tilde{I}_3 = \tilde{h}_c^3 \tilde{V}_{c_2} - \tilde{V}_{c_1}, \quad \tilde{I}_3 = \tilde{h}_c^3 \tilde{V}_{c_2} - \tilde{V}_{c_1}
\]

Based on (2) and (3), residuals \( r_1, r_2 \) and \( r_3 \) are generated as follows:

\[
\begin{align*}
\begin{cases}
    r_1 = \left( -\tilde{h}_c^1 \frac{1}{c_1} + \tilde{h}_c^1 \frac{1}{c_1} \right) I + \left( \tilde{h}_c^1 \frac{1}{c_1} - \tilde{h}_c^1 \frac{1}{c_1} \right) I \\
    r_2 = \left( -\tilde{h}_c^1 \frac{1}{c_2} + \tilde{h}_c^1 \frac{1}{c_2} \right) I + \left( \tilde{h}_c^1 \frac{1}{c_2} - \tilde{h}_c^1 \frac{1}{c_2} \right) I \\
    r_3 = \left( \tilde{h}_c^3 - \tilde{h}_c^3 \right) \frac{V_{c_1} + \left( \tilde{h}_c^3 - \tilde{h}_c^3 \right) \frac{V_{c_2} - V_{c_1}}{L} \\
        + \left( \tilde{h}_c^3 - \tilde{h}_c^3 \right) \frac{V_{c_2} - V_{c_1}}{L}
\end{cases}
\end{align*}
\]

In order to show the influence of each discrete component on the residuals, (4) is rewritten as follows:

\[
\begin{align*}
\begin{cases}
    r_1 = r_1^1 + r_1^2 \\
    r_2 = r_2^1 + r_2^2 \\
    r_3 = r_3^1 + r_3^2 + r_3^3
\end{cases}
\end{align*}
\]

where

\[
\begin{align*}
    r_1^1 &= \left( -\tilde{h}_c^1 \frac{1}{c_1} + \tilde{h}_c^1 \frac{1}{c_1} \right) I + \left( \tilde{V}_{c_1} - \tilde{V}_{c_1} \right), \\
    r_1^2 &= \left( \tilde{V}_{c_1} - \tilde{V}_{c_1} \right), \\
    r_2^1 &= \left( \tilde{V}_{c_2} - \tilde{V}_{c_2} \right), \\
    r_2^2 &= \left( \tilde{V}_{c_2} - \tilde{V}_{c_2} \right), \\
    r_3 &= \left( \tilde{I}_1 - \tilde{I}_1 \right), \\
    r_3^1 &= \left( \tilde{I}_2 - \tilde{I}_2 \right), \\
    r_3^2 &= \left( \tilde{I}_3 - \tilde{I}_3 \right) \text{ and } r_3^3 = \left( \tilde{I}_3 - \tilde{I}_3 \right) = 0.
\end{align*}
\]

### 2.4. Hybrid automata construction

Hybrid automata \( A^1 \) characterizing the hybrid dynamics of \( HC_1 \) is defined by the tuple (see Fig.4 and Fig.4):

\[
A^1 = (Q^1, \Sigma^1, SP^1, \delta^1, X^1, f_{\text{flux}}, r^1, \text{Init}^1)
\]

where,

\[
Q^1 = \{ S_1, O (S_1 \text{ opened}), S_1, C (S_1 \text{ closed}), S_1, SO \text{ (S_1 stuck opened)}, S_1, SC \text{ (S_1 stuck closed)} \} \text{ is a finite set of discrete states (discrete modes) of S_1.}
\]

The output of state \( q_k \) is characterized by the real discrete output vector \( h_k \in \{ 0 \text{ (when S_1 is opened), } 1 \text{ (when S_1 is closed)} \} \) and nominal discrete output vector \( \tilde{h}_k \). At normal discrete mode (state) \( \tilde{h}_k = h_k \) while in faulty mode \( \tilde{h}_k \neq h_k \);

\[
\Sigma^1 = \Sigma_0^1 \cup \Sigma_1^1 \text{ is the event set of S_1. It includes observable events corresponding to control command events } \Sigma_0^1 = \{ CS_1 \text{ (close S_1), } OS_1 \text{ (open S_1)} \} \text{ and unobservable events } \Sigma_1^1 \text{ including fault events } \Sigma_f^1 = \{ S_1, \text{stuck closed} \}.
\]

\[
S_{1,\text{stuck close}}, \ f_{\text{flux}}(q,\pi_{c_1}) \}
\]

\[
\delta^1: Q^1 \times \Sigma^1 \rightarrow Q^1 \text{ is the state transition function. A transition } \delta^1(q,\pi) = q^{+} \text{ corresponds to a change from state } q \text{ to state } q^{+} \text{ after the occurrence of event } \pi \in \Sigma^1.
\]

\[
X^1 = \{ V_{c_1}, V_{c_2}, I \} \text{ is a finite set of continuous variables associated to S_1.}
\]

\[
f_{\text{flux}}: Q^1 \times X^1 \rightarrow \mathbb{R}^n = \{ \tilde{X}, \tilde{X}^T \} \text{ is a function characterizing temporal evolution } \tilde{X} \text{ and nominal evolution } \tilde{X} \text{ of continuous variables } X \text{ in each discrete state } q_k, \text{ where } \tilde{X} = [\tilde{V}_{c_1}, \tilde{V}_{c_2}, \tilde{I}]^T, \tilde{X} = [\tilde{V}_{c_1}, \tilde{V}_{c_2}, \tilde{I}]^T.
\]

\[
\text{Init}^1 \subset Q^1 \times X^1 = S_1, O \text{ (} q_k^0 \text{): is the set of initial conditions.}
\]
Hybrid automata $A^2$ and $A^3$ for $HC_2$ and $HC_3$ are constructed by the same manner.

2.5. Motivation to use the considered residuals

Let us consider the occurrence of a fault of type $F_5$, e.g., $S_3$ stuck open. When the controller sends control command $C_{S_3}$ (close $S_3$), $S_3$ remains in its stick-opened mode ($\tilde{h}_q^3 = 1$ and $\tilde{h}_q^3 = 0$). The occurrence of a fault of type $F_5$ impacts at the same time $r_2$ and $r_3$ ($\tilde{h}_q^3 = 1$ and $\tilde{h}_q^3 = 0$) while it does not impact $r_1$ ($\tilde{h}_q^1 = h_q^1$, $\tilde{h}_q^2 = h_q^2$) and $C_1 = C_j$), see (4). Therefore, there is no delay of the influence of the fault occurrence on the sensitive residuals, e.g. $r_2$ and $r_3$. Moreover, there is no fault propagation from one residual to another one, from $r_2$ or $r_3$ towards $r_1$.

3. Three cell converter diagnosis

3.1. Global fault signature construction

A qualitative signature is constructed by generating continuous and discrete symbols from residual values. Continuous symbols $CS(x)$ belong to $\{0, -1, +1\}$ represent the qualitative abstraction of residual values into stable/increasing/decreasing ones:

- $r_1^0$: $r_1(t)$ belongs to the nominal interval;
- $r_1^{-}$: $r_1(t)$ is below the nominal interval;
- $r_1^{+}$: $r_1(t)$ is above the nominal interval.

The occurrence of a discrete fault exhibits an abrupt change in the continuous dynamics due to unpredicted change in $DC_j$ discrete mode. This change is characterized by the absence ($\tilde{h}_q^j = 0$ while $h_q^j = 1$) or the addition ($h_q^j = 1$ while $\tilde{h}_q^j = 0$) of associated term $e.g., \frac{f}{c^j}$. On the other hand, parametric faults due to the ageing effect cannot cause this abrupt change with a finite change in magnitude. In fact, they are indicated by a progressive abnormal change of the parameter value. In order to take into account this discriminative information, discrete symbols $DS(x)$ are added for the abstraction of each residual $r_1$ in order to distinguish between parametric and discrete faults as follows:

- $PC_j^i$ = $+Val$: denotes an abrupt positive change in residual $r_i$ due to a discrete fault caused by $DC_j$; $+Val$ is equal to the absolute value of the term associated to $h_q^j$;
- $NC_j^i$ = $-Val$: denotes an abrupt negative change in residual $r_i$ due to a discrete fault caused by $DC_j$;
- $UC_j$: denotes that there is no observed abrupt change in residual $r_i$.

- A fault signature $Sig_{q}$ at global discrete state $q$ is the combination of continuous and discrete symbols of the different residuals as follows:

$$Sig_{q} = \left( r_1^{CS(r_1)}, DS(r_1) \right) \& \ldots \& \left( r_n^{CS(r_n)}, DS(r_n) \right)$$

(7)

3.2. Local fault signature construction

Each discrete state $q_k^j$ of $A_j$ generates a fault signature $sig_k^j$ as a guard over residuals $r^j$ calculated in this discrete state as follows:

$$sig_k^j = \left( r_1^{CS(r_1)}^j, DS(r_1^j) \right) \& \ldots \& \left( r_n^{CS(r_n)}^j, DS(r_n^j) \right)$$

(8)

Based on (5), we can write:

$$r_1 = \tilde{x}_i - \hat{x}_i = (\tilde{x}_1^i - \hat{x}_1^i) + \ldots + (\tilde{x}_n^j - \hat{x}_n^j) = r_1^i + \ldots + r_1^n$$

If $\left(\tilde{x}_i^j - \hat{x}_i^j\right) = r_1^i \neq 0$, it means that the other parts of residual $r_i$ are equal to zero (one fault can be occurred at the same time). In this case, $r_i = r_1^i$. Hence, $r_i$ will have the continuous and discrete symbols of $r_1^i$. Thus (8) is rewritten as follows:

$$sig_k^j = \left( r_1^{CS(r_1)}^j, DS(r_1^j) \right) \& \ldots \& \left( r_n^{CS(r_n)}^j, DS(r_n^j) \right)$$

(9)

By comparing (8) and (9), we can notice that $sig_k^j$ becomes equivalent to the global fault signature $Sig_{q}$.

3.3. Local hybrid diagnoser

The objective of a local hybrid diagnoser $D_j$ is to detect and isolate the occurrence of parametric and discrete faults affecting the dynamics of hybrid component $HC_j$. $D_j$ is built based on the local model, $A^j$, of $HC_j$. Each state of $D_j$, denoted $z_k^j$, is of the form shown in Fig.5.

![Figure 5. State of local hybrid diagnoser $D_j$ of $HC_j$.](image)

Local hybrid diagnoser $D_1$ of $HC_1$ is depicted in Fig.6. It is constructed from hybrid automata $A^j$ of Fig.4.

$D_1$ is constructed as follows:

- Initial state $z_1^1$, characterized by $(Q_1^1, \tilde{Q}_1^1, SP^1)$, is composed of the following $A^1$ states: $q_1^1$ ($A^1$ initial state), $q_1^2$ reached from $q_1^1$ by the occurrence of a fault event ‘$S_{1-stuck-open}$’ (fault of type $F_1$) and $q_1^3$ reached from $q_1^1$ due to the occurrence of a fault event ‘$f \neq x_1^1$’ (fault of type $F_2$). Thus, $Q_1^1$ is equal to $\{q_1^1, q_1^2, q_1^3\}$. $SP^1$ gathers the normal and fault labels associated to the states belonging to $Q_1^1$. Therefore, $SP^1$ is equal to $\{N_1, F_1, F_2\}$. 269
Finally, $\tilde{X}_k^1$ gathers $\tilde{X}_k^1$ of all the states $q_1^1$ of $Q_1^1$. Since states $q_1^1 \cup q_1^2 \cup q_1^3$ are reached from $q_1^1$ due to the occurrence of unobservable event (a fault), $\tilde{X}_k^1$, $\tilde{X}_k^2$ and $\tilde{X}_k^3$ are equivalent and equal to $[0 \ 0 \ 0]^T$ (see Fig.4).

- The states of $D_1$ reached due to the occurrence of each control command event observed by $HC_1$ are computed. Since $D_1$ initial state is $S_1$, a control command $OS_1$ will not change $D_1$ state $z_1^1$. The event $CS_1$ transits $D_1$ from $z_1^1$ to $z_1^2$, characterized by ($Q_1^1$, $\tilde{X}_1^1$, $SP_1^1$). $Q_2^1$ is equal to all the states reached from $Q_1^1$ due to the occurrence of $CS_1$. Thus, $Q_2^1$ is equal to $\{q_2^1, q_4^1, q_8^1\}$ (see Fig.4).

- Fault signatures are generated for each $D_1$ state thanks to the continuous dynamic evolution in each discrete state of $Q_1^1$. In the initial $D_1$ state, $z_1^1$, the continuous dynamic evolution in any state of $Q_1^1$ does not evolve. Therefore, their associated residuals are equal to zero leading to obtain the fault signature $Sig_{\tilde{X}^1}$ (see Table 2). In $z_1^2$, the continuous dynamic evolution of the states belonging to $Q_1^1$ will allow to generate four fault signatures as we can see in Fig.6. They allow to detect and isolate discrete and parametric faults $F_1$ and $F_7$ as follows. $q_3^1$ of $A^1$ (reached due to the occurrence of fault of type $F_1$) generates local fault signature $Sig_{q_3}$.

$$Sig_{q_3} = \left( r_1^{+ \frac{V_{C_1}}{L}}, DS(r_1) \right) \& \left( r_2^{+ \frac{V_{C_1}}{L}}, DS(r_2) \right) \& \left( r_3^{+ \frac{V_{C_1}}{L}}, DS(r_3) \right).$$

This global signature is used as transition to isolate the occurrence of a fault of type $F_1$. Same reasoning can be applied for the other fault signatures. To overcome the noise problem, the values of comparison (e.g. $\frac{1}{C_2}$) are replaced by the intervals corresponding to the selected confidence level. These intervals are calculated using Z-test in order to determine the thresholds of each value.

Same reasoning can be followed for the construction of the other states of $D_1$.

It is worth pointing out that $Sig_q = Sig_{q_3} = \left( r_1^{+ \frac{V_{C_1}}{L}}, DS(r_1) \right) \& \left( r_2^{+ \frac{V_{C_1}}{L}}, DS(r_2) \right)$ means that the three conditions have to be satisfied in order to enable the corresponding transition.

Table II shows the local fault signatures (equivalent to the global fault signatures) used by $D_1$ to achieve its local diagnosis.

<table>
<thead>
<tr>
<th>$SP_1$</th>
<th>Local signature name</th>
<th>Equivalent global fault signatures</th>
</tr>
</thead>
<tbody>
<tr>
<td>$F_1$</td>
<td>$Sig_{q_1}^1$</td>
<td>$(r_1^{+ \frac{V_{C_1}}{L}}, DS(r_1)) &amp; (r_2^{+ \frac{V_{C_1}}{L}}, DS(r_2))$</td>
</tr>
<tr>
<td>$F_2$</td>
<td>$Sig_{q_2}^1$</td>
<td>$(r_1^{+ \frac{V_{C_1}}{L}}, DS(r_1)) &amp; (r_2^{+ \frac{V_{C_1}}{L}}, DS(r_2))$</td>
</tr>
<tr>
<td>$F_3$</td>
<td>$Sig_{q_3}^1$</td>
<td>$(r_1^{+ \frac{V_{C_1}}{L}}, DS(r_1)) &amp; (r_2^{+ \frac{V_{C_1}}{L}}, DS(r_2))$</td>
</tr>
<tr>
<td>$N_1$</td>
<td>$Sig_{q_4}^1$</td>
<td>$(r_1^{+ \frac{V_{C_1}}{L}}, DS(r_1)) &amp; (r_2^{+ \frac{V_{C_1}}{L}}, DS(r_2))$</td>
</tr>
</tbody>
</table>

The other diagnosers $D_2$ and $D_3$ for $HC_2$ and $HC_3$ can be constructed similarly as for $D_1$. $D_2$ is sensitive to discrete faults $F_3$ and $F_4$ and to parametric faults $F_7$ and $F_9$, while $D_3$ is sensitive to discrete faults $F_5$ and $F_6$ and to parametric fault $F_8$. The occurrence of parametric fault $F_7$ (respectively $F_9$) is detected intrinsically by $D_1$ and $D_2$ (respectively $D_2$ and $D_3$).

### 3.4. Coordinator construction

The system decomposition achieved by the proposed approach allows each local hybrid diagnoser to diagnose faults that can occur in its corresponding hybrid component. In order to obtain a decentralized diagnosis performance equivalent to a centralized diagnoser, a decision coordinator is defined. It generates a global diagnosis decision by merging local diagnosis decisions provided by local hybrid diagnosers. Let us denoted $F^3$, $F^2$ and $F^1$ the faults that can...
occur, respectively, in \( HC_1, HC_2 \) and \( HC_3 \). \( F^1 \in \{F_1, F_2, F_7\} \), \( F^2 \in \{F_3, F_4, F_7, F_8\} \) and \( F^3 \in \{F_5, F_6, F_9\} \). Global diagnosis decision \( DD \) is computed as follows:

- \( D_1 \) diagnoses with certainty the occurrence of a fault of type \( F^1 \) through the global fault signature \( \Sigma g_4 \), \( D_2 \) cannot diagnose with certainty the occurrence of this fault because it does not belong to its associated \( HC_2 \). \( D_3 \) cannot diagnose with certainty the occurrence of this fault because it does not belong to its associated \( HC_3 \). Therefore, the global diagnosis decision will be \( DD = F^1 \).

- Global fault signature \( \Sigma g_4 \) corresponds to a fault of type \( F^1 \) or of type \( F^2 \) (\( F_7 \)). Thus, global diagnoser \( DD \) will be \( F^1 \) or \( F^2 \). Both \( D_1 \) and \( D_2 \) are sensitive to this fault signature, therefore \( D_1 \) declares \( F_7 \); and \( D_2 \) declares \( F_7 \). In order to obtain a decentralized diagnosis decision equivalent to the global one, global diagnosis decision \( DD \) will be equal to (\( F^1 \) or \( F^2 \)) = \( F_7 \).

- Table 3 shows global diagnosis decision \( DD \). A local diagnoser declares ‘nothing’ when it cannot confirm the occurrence or the non-occurrence of a fault.

### Table 3. Global diagnosis decision \( DD \) for Three Cell Converter

<table>
<thead>
<tr>
<th>cases</th>
<th>Local diagnoser ( D_1 )</th>
<th>Local diagnoser ( D_2 )</th>
<th>Local diagnoser ( D_3 )</th>
<th>Global decision ( DD )</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>( N_1 )</td>
<td>( N_2 )</td>
<td>( N_3 )</td>
<td>( N )</td>
</tr>
<tr>
<td>2</td>
<td>( F^1 )</td>
<td>( F_2 )</td>
<td>( F_3 )</td>
<td>( F^1 )</td>
</tr>
<tr>
<td>3</td>
<td>( F_1 )</td>
<td>( F^2 )</td>
<td>( F_3 )</td>
<td>( F^2 )</td>
</tr>
<tr>
<td>4</td>
<td>( F_1 )</td>
<td>( F^2 )</td>
<td>( F_3 )</td>
<td>( F^3 )</td>
</tr>
<tr>
<td>5</td>
<td>( N_1 )</td>
<td>( F_2 )</td>
<td>( F_3 )</td>
<td>( F^3 )</td>
</tr>
<tr>
<td>6</td>
<td>( N_1 )</td>
<td>( N_2 )</td>
<td>( F_3 )</td>
<td>( F^3 )</td>
</tr>
<tr>
<td>7</td>
<td>( N_1 )</td>
<td>( N_2 )</td>
<td>( N_3 )</td>
<td>( N )</td>
</tr>
</tbody>
</table>

### 3.5. Identification of parametric faults

When one of parametric faults is diagnosed, its real value needs to be identified. As an example, for parametric fault of type \( F_7 \) related to \( C_1 \), the real value of the latter is identified based on its corresponding residual as follows:

\[
\begin{align*}
  r_1 &= \left( -\frac{1}{C_1} + \frac{1}{C_1} \right) \Rightarrow \bar{C}_1 = \frac{C_1}{C_1 / \bar{r}_1 + 1} \quad (10) \\
  r_2 &= \left( +\frac{1}{C_1} - \frac{1}{C_1} \right) \Rightarrow \bar{C}_1 = \frac{C_1}{C_1 / \bar{r}_2 - 1} \quad (11)
\end{align*}
\]

The same reasoning is applied to identify the real value of capacitor \( C_2 \) in case of fault of type \( F_8 \) related to \( C_2 \).

### 4. EXPERIMENTATION AND OBTAINED RESULTS

In order to evaluate the proposed approach, simulations were carried out for the three-cell converter using Matlab-Simulink™ environment and Stateflow™ toolbox. The parameters used in these simulations are:

\[
E = 60V, \bar{C}_1 = \bar{C}_2 = 40\mu F, R = 200\Omega, L = 0.1H.
\]

In order to highlight the efficiency of the diagnoser, the simulations take into account the set of faults defined in Table 1 for the three-cell converter.

Discrete controller commands are assured by a pulse width modulation (PWM) signal (Defoort et al., 2011). Fig.7 depicts the control of three switches \( S_1, S_2 \) and \( S_3 \). When the triangular signal is below the reference signal (ref in Fig.7), the associated switch is controlled to be opened. When the triangular signal is above the reference signal, the associated switch is controlled to be closed. This sequence of control is periodic with a period of \( T_{PWM} = 0.02 \) s.

![Figure 7. PWM for control of three switches \( S_1, S_2 \) and \( S_3 \).](image)

### 4.1. Normal conditions scenario

Fig.8 depicts, respectively, the signals of floating voltages \( V_{C_1} \) and \( V_{C_2} \) and the current \( I \). These signals correspond to the normal conditions. Moreover, one can see in Fig.8 that \( V_{C_1} \) (respectively \( V_{C_2} \)) has a periodic signal corresponding to load and unload of capacitor \( C_1 \) (respectively \( C_2 \)) around the mean value \( V_{C_{1ref}} = \frac{E}{3} = 20V \) (respectively \( V_{C_{2ref}} = \frac{2E}{3} = 40V \)) and that the current \( I \) remains constant in the region of its reference value (0.15A).

Fig.9 shows the real and nominal dynamic evolution of \( V_{C_1} \) (\( V_{C_1} \) and \( \bar{V}_{C_1} \)), \( V_{C_2} \) (\( V_{C_2} \) and \( \bar{V}_{C_2} \)) and \( I \). We can notice that the curves representing the real and nominal dynamic evolutions are superposed. Consequently, residuals \( r_1, r_2 \) and \( r_3 \) are equal to zero in these conditions.

![Figure 8. Real signals corresponding to \( V_{C_1}, V_{C_2} \) and \( I \) in normal conditions.](image)
4.2. Faulty conditions scenario

The test scenario is generated as follows (see Fig.10). Each fault \( f \), belonging to one of the fault labels of Table 1, is generated starting at time \( t_{sf} \) and ending at time \( t_{ef} \). Then, the system returns to normal operating conditions before generating a new fault for a certain time. Parametric faults of types \( F_2 \) and \( F_8 \) are simulated by changing gradually the real values of \( C_1 \), respectively \( C_2 \), in positive or negative direction using a ramp signal. \( V_{C_1} \), \( V_{C_2} \) and \( I \) simulated signals including these faults are represented in Fig. 11.

One can see in Fig.11 that \( V_{C_1} \) (respectively \( V_{C_2} \)) has lost the periodic aspects in the case of fault and that the current \( I \) has become nonconstant in the region of its reference value.

\( r_1, r_2, r_3 \) are represented in Fig.12 and Fig.13. As expected, \( r_1 \) is sensitive to the faults of types \( F_1, F_2, F_3, F_4 \) and \( F_5 \), \( r_2 \) is sensitive to the faults of types \( F_3, F_4, F_5, F_6 \) and \( F_8 \) while \( r_3 \) is sensitive to the faults of types \( F_1, F_2, F_3, F_4, F_5 \) and \( F_6 \).

Fig.14, Fig.15, Fig.16 and Fig.17 show, respectively, local decision \((SP_1)\) of diagnoser \( D_1 \), local decision \((SP_2)\) of diagnoser \( D_2 \), local decision \((SP_3)\) of diagnoser \( D_4 \) and global decision \((SP)\).

The first local diagnoser \( D_1 \) is sensitive to faults of types \( F_1, F_2 \) and \( F_7 \) (diagnosis with certainty their occurrence), the second local diagnoser \( D_2 \) is sensitive to faults of types \( F_3, F_4, F_7 \) and \( F_8 \) while the third local diagnoser \( D_3 \) is sensitive to faults of types \( F_5, F_6 \) and \( F_8 \). We can conclude that the global decision indicates with certainty the occurrence of each of the generated faults. The diagnosis delay corresponds to the time when the system is in a discrete fault is due to residues that are silent in some discrete state.
4.3. Normal conditions with noises in parameters scenario

Diagnosis algorithms should be tested and evaluated on real systems with practical significance. In these systems, factors such as noise make diagnosis challenging. Therefore, there is a need to evaluate the robustness of the diagnosis algorithms for different fault and noise magnitudes.

Accurate simulation models of the system are required for this purpose. Further, it is important to execute the diagnosis algorithms on systems, where model uncertainty is always present, and complicates the diagnosis task. In order to examine the robustness of our approach, a parametric noise (see for example Fig.18), applied on parameters, is used. From an electrical point of view, the resistors are the most disturbing element in tree cell converter systems. For this
reason, we simulated noise on signal resistance.

![Resistance noise](image)

Figure 18. Noise added to resistance R in the converter.

In order to take into account the noises in R, the residuals of (4) is written as follows:

\[
\begin{align*}
    r_1 &= \left( -\hat{h}_q^1 \frac{1}{C_1} + \hat{h}_q^1 \frac{1}{C_1} \right) I + \left( \hat{h}_q^2 \frac{1}{C_2} - \hat{h}_q^2 \frac{1}{C_2} \right) I \\
    r_2 &= \left( -\hat{h}_q^2 \frac{1}{C_2} + \hat{h}_q^2 \frac{1}{C_2} \right) I + \left( \hat{h}_q^3 \frac{1}{C_3} - \hat{h}_q^3 \frac{1}{C_3} \right) I \\
    r_3 &= (-\bar{R} + R_b) \frac{1}{L} + \left( \hat{h}_q^1 - \hat{h}_q^1 \right) \frac{1}{l} + \left( \hat{h}_q^2 - \hat{h}_q^2 \right) \frac{1}{l} + \left( \hat{h}_q^3 - \hat{h}_q^3 \right) \frac{1}{l}
\end{align*}
\]

(12)

Where \( \bar{R} \) is the nominal value of R without noises while \( R_b \) is the real value of R. The latter corresponds to the nominal value of R with noises.

\( r_1, r_2, r_3 \) are represented in Fig 19. As expected, \( r_3 \) and \( r_2 \) are not sensitive to this perturbation in normal conditions (\( \bar{R} \) does not influence the dynamic evolution of \( Vc_1 \) and \( Vc_2 \). While \( r_3 \) is impacted by this noise. It changes between \(-0.4A/s\) and \(0.4A/s\).

![Residuals](image)

Figure 19. Set of residuals with noise corresponding to the normal conditions.

Ideally, any non-zero residual value implies a fault, which should trigger the fault isolation system. Therefore, statistical techniques are required for reliable fault detection. The fault detection system is based on a Z-test that uses the estimated variance of the residuals and a pre-specified confidence level to establish the significance of observed nonzero residuals. To cope with noise, we compute the mean and the variance at different time points (Biswas et al., 2003). The Z-test is a statistical inference test employed to establish the significance of the deviation. It requires the mean and standard deviation of the population, and the mean and size of the samples. These values are estimated using sliding windows over the residual for a variable. A small sliding window of size \( W_1 = 5 \) samples, is used to estimate the current mean \( \mu_{r_1}(t) \) of the residual \( r_1 \) related to the variable \( x_i \):

\[
\mu_{r_1}(t) = \frac{1}{W_2} \sum_{v=t-W_1+1}^{t} r_1(v)
\]

(13)

We suppose the mean of the population is equal to zero, since the residual should be zero when the system is free of faults. We compute the variance from data history of the nominal residual signal over a window \( W_2 \) proceeding \( W_1 \) as an estimate of the true variance:

\[
\sigma_{r_1}(t) = \frac{1}{W_2} \sum_{v=t-W_2-W_1+1}^{t} \left( \eta(v) - \mu_{r_1}(v) \right)^2
\]

(14)

The size of \( W_2 \) must contain enough of measurements in order to estimate correctly the residuals’ mean and variance in the normal operating conditions and therefore to reduce the rate of false alarms. The size of \( W_1 \) must also be selected as a tradeoff between the delay of fault detection and the rate of false alarms. The size of \( W_2 \), respectively \( W_1 \), is chosen experimentally to be equal to 25, respectively 5, measurements.

Since the distribution of residuals mean is supposed to follow the normal distribution, a confidence level, \( \alpha \), is defined by determining the bound \( [\mu_{r_1} - \mu_{r_1}] \) within which \( \mu_{r_1}(t) \) is considered to correspond to normal operating conditions. \( [\mu_{r_1} - \mu_{r_1}] \) is defined using Z-test table and the approximation \( \sigma_{r_1} \):

\[
\mu_{r_1} = \frac{z_{\alpha/2} \sigma_{r_1}}{\sqrt{W_1}}
\]

(16)

\[
\mu_{r_1} = \frac{z_{\alpha} \sigma_{r_1}}{\sqrt{W_1}}
\]

(17)

For \( \alpha \) equal to 0.95, \( z_{\alpha/2} \) and \( z_{\alpha} \) are equal to, respectively, 1.64 and 1.64.

The Z-test is employed in the following manner:

\[
\mu_{r_1} < \mu_{r_1} < \mu_{r_1} \Rightarrow \text{No fault}
\]

Otherwise \( \Rightarrow \text{Fault} \)

Fig 20 depicts mean of residuals \( \mu_{r_3} \) and the negative and positive threshold of this residual. The mean and true variance of residual \( r_1 \) and \( r_2 \) are equal to zero. Thus its threshold is also equal to zero (\( \mu_{r_1}, \mu_{r_1}^{\text{+}} \) and \( \mu_{r_1}^{\text{-}} \), respectively, \( \mu_{r_2}, \mu_{r_2}^{\text{+}} \) and \( \mu_{r_2}^{\text{-}} \)).
Table 4. Local fault signatures generated due to the occurrence of faults in HC1 in case of parametric noise.

<table>
<thead>
<tr>
<th>SP1</th>
<th>Local signature name</th>
<th>Equivalent global fault signatures</th>
</tr>
</thead>
<tbody>
<tr>
<td>$F_1$</td>
<td>$Sig_{11}$</td>
<td>$(\frac{\mu_i}{\mu_1} &gt; \mu_2) &amp; (\mu_2 &lt; \mu_3 &lt; \mu_i) &amp; (\frac{\mu_i}{\mu_1} &lt; \mu_3 + \mu_2)$</td>
</tr>
<tr>
<td>$F_2$</td>
<td>$Sig_{12}$</td>
<td>$(\frac{\mu_i}{\mu_1} &gt; \mu_2) &amp; (\mu_2 &lt; \mu_3 &lt; \mu_i) &amp; (\frac{\mu_i}{\mu_1} &lt; \mu_3 + \mu_2)$</td>
</tr>
<tr>
<td>$F_3$</td>
<td>$Sig_{13}$</td>
<td>$(\mu_i &lt; \mu_3) &amp; (\mu_2 &lt; \mu_3 &lt; \mu_i) &amp; (\mu_2 &lt; \mu_3 &lt; \mu_i)$</td>
</tr>
<tr>
<td>$F_4$</td>
<td>$Sig_{14}$</td>
<td>$(\mu_i &lt; \mu_3) &amp; (\mu_2 &lt; \mu_3 &lt; \mu_i) &amp; (\mu_2 &lt; \mu_3 &lt; \mu_i)$</td>
</tr>
</tbody>
</table>

The other diagnosers $D_2$ and $D_3$ for HC2 and HC3 can be constructed similarly as for $D_1$.

4.4. Faulty conditions with parameters perturbation

In order to evaluate the proposed approach in case of noise, another scenario of fault is generated (see Fig.21). The corresponding $\mu_1$, $\mu_2$, $\mu_3$ for this scenario are represented in Fig.22 and Fig.23. In this case, noises are observed only in $r_3$ at normal and faulty conditions (see zoom in Fig.24). As we said before, only $r_3$ is impacted by noises since the noisy parameter $R$ is included only in dynamic evolution $I$ of $I$ (see (1)). To overcome this problem, a threshold is defined for each residual using Z-test. These thresholds are used during the fault detection and isolation in order to avoid the false alarms as well as the fault missed detection caused by noises.

Fig.24, Fig.25, Fig.26 and Fig.27 show, respectively, local decision ($SP_1$) of diagnoser $D_1$, local decision ($SP_2$) of diagnoser $D_2$, local decision ($SP_3$) of diagnoser $D_3$ and global decision ($SP$). The first local diagnoser $D_1$ is sensitive to faults of types $F_1$, $F_2$ and $F_3$ (diagnosis with certainty their occurrence), the second local diagnoser $D_2$ is sensitive to faults of types $F_2$, $F_4$, $F_7$ and $F_9$ while the third local diagnoser $D_3$ is sensitive to faults of types $F_5$, $F_6$ and $F_8$. We can conclude that the global decision indicates with certainty the occurrence of each of the generated faults regardless of the existence of noise.
5. CONCLUSION
In this paper, a decentralized hybrid diagnosis approach for discretely controlled continuous systems is proposed. The elaboration of this approach is motivated by the capacity of the hybrid models to represent intrinsically the interactions between the continuous and the discrete dynamics of a system.

The originality of this work is the exploitation of the system modularity in order to reduce its complexity as well as the explosion in the number of its discrete states. To achieve that, the diagnosis task is accomplished by a set of local hybrid diagnosers. Each of the latter is responsible of the diagnosis of a specific part of the system. These local hybrid diagnosers are built without the use of the system global model but only local models. The decisions of the local hybrid diagnosers are merged using a coordinator in order to obtain a diagnosis performance equivalent to the one of a centralized diagnosis structure.

In the future work, this approach will be applied to a real
three-cell converter. Then, it will be developed to consider multiple and adjacent faults in a more general class of hybrid dynamic systems.

REFERENCES


BIographies

Hanane Louajri received her Master degree in Complex Systems Engineering section Automatic and Embedded data Processing from the University of Nancy in 2011. She received his engineering degree in Automatic and Computer Engineering from the High Engineering School “Ecole Marocaine des Sciences de l’Ingénieur” in 2011. She is currently PhD student in the High National Engineering School of Mines “École Nationale Supérieure des Mines de Douai” at the Department of Automatic Control and Computer Science. Her research interests are diagnosis of hybrid dynamic systems.

Moamar Sayed-Mouchaweh received his Master degree from the University of Technology of Compiègne-France in 1999. Then, he received his PhD degree from the University of Reims-France in December 2002. He was nominated as Associated Professor in Computer Science, Control and Signal processing at the University of Reims-France in the Research center in Sciences and Technology of the Information and the Communication (CReSTIC). In December 2008, he obtained the Habilitation to Direct Researches (HDR) in Computer science, Control and Signal processing. Since September 2011, he is working as a Full Professor in the High National Engineering School of Mines “École Nationale Supérieure des Mines de Douai” at the Department of Automatic Control and Computer Science (Informatique & Automatique 1A).