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To cite this version:
Carlos Gustavo Pérez Zuniga, J Sotomayor-Moriano, Elodie Chantery, Louise Travé-Massuyès, M. Soto. Flotation Process Fault Diagnosis Via Structural Analysis. 18th IFAC Symposium on Control, Optimization and Automation in Mining, Mineral and Metal Processing (MMM 2019), Aug 2019, Stellenbosch, South Africa. hal-02189499

HAL Id: hal-02189499
https://hal.laas.fr/hal-02189499
Submitted on 19 Jul 2019

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Flotation Process Fault Diagnosis Via Structural Analysis

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Abstract: For the improvement of safety and efficiency, fault diagnosis becomes increasingly important in mining industry. The expansion of flotation processes with high-tonnage cooper concentrators demands the use of large flotation circuits in which the large amount of instrumentation and interconnected subsystems (with coupled measured and non-measured variables) makes this process complex. Moreover, in a flotation process, any equipment failure can lead to a fault condition, which will affect the operation of this process. This paper proposes an approach for on-line fault diagnosis useful for a large flotation circuit based on a distributed architecture. In this approach, structural analysis is used for the design of the distributed fault diagnosis system. Finally, a procedure for the implementation of local diagnosers for on-line operation is presented and illustrated with an application to a flotation process.

Keywords: Fault diagnosis, Flotation process, Distributed architecture, Structural analysis

1. INTRODUCTION

Nowadays, the recovery is one of the most important process in mining industry. Currently, the recovery of minerals in this industry is mainly made through the flotation processing technique around the world.

Froth flotation uses the difference in surface properties to physically separate minerals from gangue and is one of the most widely used methods of ore concentration. In order to improve the recovery of valuable minerals, industrial flotation practice uses multiple cells. These cells are arranged in series forming a bank. A combination of banks is referred as flotation circuit. It is common for conventional flotation cells to be assembled in a circuit, with rougher, cleaner, and scavenger cells, which can be arranged in a designed configuration. On the other hand, in recent decades, the expansion of flotation with high-tonnage copper concentrators in Peru, Chile, etc. (O’Connell et al., 2016), has been demanding the use of large flotation circuits consisting of a large number of banks, with several cells each one.

Flotation equipment requires a machine for mixing and dispersing air throughout the mineral slurry while removing the froth product. Instrumentation is also necessary for a successful implementation of control strategies. The ultimate aim of control is to increase the economic efficiency of the process by seeking to optimise performance, and there are several strategies which can be adopted to achieve this, (Wills, 2006). In the flotation process, any equipment failure (in valves, sensors, pipelines, etc.), can lead to a fault condition, which will affect the operation of this process. In (Xu et al., 2012; Ming et al., 2015), methodologies for fault detection in flotation process operation that use analysis of variables measurement are proposed. The use of Principal Component Analysis (PCA) models is proposed in (Bergh and Acosta, 2009) to detect instrumentation failures on a flotation column. The development of fault diagnosis systems in mining industry is very important because an effective diagnosis of faults may have a high economic and safety impact. However, fault diagnosis in large flotation circuits is a difficult task due not only to the large amount of instrumentation, but also to its interconnected subsystems with coupled (measured and non-measured) variables between them. In this case, the implementation of a global diagnoser may be an impractical option because of the amount of needed communication, (Blanke et al., 2016). Thus the use of centralized architecture for on-line fault diagnosis can be very expensive and lack robustness for large-scale interconnected subsystems, (Pérez-Zuñiga et al., 2018). One possibility to overcome this difficulty is to employ a distributed diagnosis architecture.

Recently, a distributed diagnosis framework for physical systems with continuous behavior using structural model has been proposed in (Bregon et al., 2014) and a distributed diagnosis approach with a set of diagnosers that are as local as possible was presented in (Khorasgani et al., 2015). In distributed diagnostic architectures, unlike centralized ones, it is not mandatory to know the model of the global system. Distributed architectures use subsystem models for diagnosis and local diagnosers (LDs), so they would be more appropriate for complex systems, (Pérez-Zuñiga et al., 2017), such as the large flotation circuits.

The aim of this paper is to propose an approach for online fault diagnosis in flotation process circuit based on a
distributed architecture propose in (Pérez-Zumiga et al., 2017). In this approach, structural analysis is used as an efficient tool for the design of fault diagnosis systems for nonlinear processes. (Isermann, 2006). Likewise, in order to optimize the offline design of LDs, Fault-Driven Minimal Structurally Overdetermined (FMSO) sets are calculated and guarantee minimal redundancy of analytical redundancy relations (ARR) generators, (Pérez-Zumiga et al., 2015). At last, a procedure for the residual generation for on-line operation is presented and shown with the flotation process.

2. PROBLEM STATEMENT

In a flotation process, the pulp is introduced into the first cell, the froth is collected through launders and the remaining pulp flows to the next cell. The magnitude of the flow depends on the pressure difference between two adjacent cells, the position of the control valves, and the viscosity and density of the pulp. Figure 1 shows the flotation process under study.

![Diagram of the flotation process under study.](image)

Due to the physical characteristics of the flotation process, and considering the disturbances caused by the composition of the minerals and the constant and arduous work of the system, these systems usually have a limited efficiency, which is evidenced by faults in sensors, actuators and the system such as leaks in tanks and pipes, (Jamsa et al., 2003).

For the application of the structural analysis approach, let the system description consist of a set of $n$ equations involving a set of variables partitioned into a set $Z$ of $n_Z$ known (or measured) variables and a set $X$ of $n_X$ unknown (or unmeasured) variables. We refer to the vector of known variables as $z$ and the vector of unknown variables as $x$. The system may be impacted by the presence of $n_f$ faults that appear as parameters in the equations. The set of faults is denoted by $F$ and we refer to the vector of faults as $f$.

**Definition 1.** (System). A system, denoted $\Sigma(z, x, f)$ or $\Sigma$ for short, is any set of equations relating $z$, $x$, and $f$. The equations $e_i(z, x) \subseteq \Sigma(z, x, f)$, $i = 1, \ldots, n$, are assumed to be differential or algebraic in $z$ and $x$.

The flotation process under study has 5 levels at different altitudes ($h_1$ to $h_5$) and is composed of 41 equations (36 for the system and 5 linked to the level control of each stage). Later, we assumed each level with outlet pipe as a subsystem so this system is composed by 5 subsystems. The flow $q_{in}$ refers to the pulp inflow, while the flow $q_{out}$ is related to the tailings. There are a set of 5 measurements $y_1$ to $y_5$ and a set of 5 control valves $u_1$ to $u_5$.

3. BACKGROUND THEORY

In this section, we summarize some important concepts presented in previous works related to the generation of diagnostic tests using structural analysis. Structural analysis allows to obtain structural models that are very useful for the design of Model Based Diagnosis (MBD) systems. The main assumption is that each system component is described by one or several constraints; thereby, violation of at least one constraint indicates that the system component is faulty.

The structural model of the system $\Sigma(z, x, f)$, also denoted with some abuse of notation by $\Sigma(z, x, f)$ or $\Sigma$ in the following, can be obtained abstracting the functional equations. It retains a representation of which variables are involved in the equations. This abstraction leads to a bipartite graph $G(\Sigma \cup X \cup Z, A)$, or equivalently to $G(\Sigma \cup X, A)$, where $A \subseteq X$ and $A$ is a set of edges such that $a(i, j) \in A$ iff variable $x_i$ is involved in equation $e_j$.

The structural model $\Sigma(z, x, f)$ for this system is composed of 41 equations $e_1$ to $e_{41}$ relating the known variables $Z = \{u_1, u_2, \ldots, u_5, y_1, y_2, \ldots, y_5, q_{in}, q_{out}\}$, the unknown variables $X = \{\dot{x}_1, \dot{x}_1, \dot{x}_2, \dot{x}_2, \dot{x}_3, \ldots, \dot{x}_8, \dot{x}_8, \dot{q}_0, q_1, q_2, \ldots, q_8\}$ and the set of sensors, actuators and process faults $F = \{f_1, f_2, f_3, f_4, f_5, \ldots, f_{16}\}$.

3.1 Analytical Redundancy Relations

Analytical redundancy relations (ARR) are equations that are deduced from an analytical model and only involve measured variables.

**Definition 2.** (ARR for $\Sigma(z, x, f)$). Let $\Sigma(z, x, f)$ be a system. Then, a relation $\text{arr}(z, \dot{z}, \ldots) = 0$ is an ARR for $\Sigma(z, x, f)$ if for each $z$ consistent with $\Sigma(z, x, f)$ the relation is fulfilled.

**Definition 3.** (Residual generator for $\Sigma(z, x, f)$). A system taking a subset of the variables $z$ as input, and generating a scalar signal $\text{arr}$ as output, is a residual generator for the model $\Sigma(z, x, f)$ if, for all $z$ consistent with $\Sigma(z, x, f)$, it holds that $\lim_{t \to \infty} \text{arr}(t) = 0$.

We use the decomposition of Dulmage Mendelshon as a tool to compute redundant sets using structural analysis, (Duhamel and Mendelsohn, 1958). Making use of this permutation, a system model $\Sigma$ can be divided into three parts: the structurally overdetermined (SO) part $\Sigma^+$ with more equations than unknown variables; the structurally just determined part $\Sigma^j$, and the structurally underdetermined part $\Sigma^-$ with more unknown variables than equations, (7).

**Definition 4.** (Structural redundancy). The structural redundancy $\rho_{\Sigma'}$ of a set of equations $\Sigma' \subseteq \Sigma$ is defined as the difference between the number of equations and the number of unknown variables in $\Sigma'$.

**Definition 5.** (Fault support). The fault support $F_{\Sigma'}$, of a set of equations $\Sigma' \subseteq \Sigma$ is defined as the set of faults that are involved in the equations of $\Sigma'$.
Definition 6. (PSO and MSO sets). A set of equations $\Sigma$ is proper structurally overdetermined (PSO) if $\Sigma = \Sigma^+$ and minimally structurally overdetermined (MSO) if no proper subset of $\Sigma$ is overdetermined (Krysander et al. (2010)).

Since PSO and MSO sets have more equations than variables, they can be used to generate ARRs and residuals. A Fault-Driven Minimal Structurally Overdetermined (FMSO) set can be defined as an MSO set of $\Sigma(z,x,f)$ whose fault support is not empty.

Let us define $Z_\varphi \subseteq Z$, $X_\varphi \subseteq X$, and $F_\varphi \subseteq F$ as the set of known variables, unknown variables involved in the FMSO set $\varphi$, and its fault support, respectively. Next, we summarize the definition of FMSO set,

Definition 7. (FMSO set). A subset of equations $\varphi \subseteq \Sigma(z,x,f)$ is an FMSO set of $\Sigma(z,x,f)$ if (1) $F_\varphi \neq \emptyset$ and $\rho_\varphi = 1$ that means $|\varphi| = |X_\varphi| + 1$, (2) no proper subset of $\varphi$ is overdetermined. (Pérez-Zumiga et al. 2017)

We propose the use of FMSO sets that guarantee to always be impacted to faults contrary to the MSO sets that not may not be impacted by faults. Based on the concept of FMSO set, we summarize the concept of detectable fault, and isolable fault:

Definition 8. (Detectable fault). A fault $f \in F$ is detectable in the system $\Sigma(z,x,f)$ if there is an FMSO set $\varphi \in \Phi$ such that $f \notin F_\varphi$.

Definition 9. (Isolable fault). Given two detectable faults $f_j$ and $f_k$ of $F$, $j \neq k$, $f_j$ is isolable from $f_k$ if there exists an FMSO set $\varphi \in \Phi$ such that $f_j \in F_\varphi$ and $f_k \notin F_\varphi$.

Additionally, a Clear Minimal Structurally Overdetermined (CMSO) set is a MSO set of $\Sigma(z,x,f)$ whose fault support is empty.

3.2 Distribution and Related Notions

A distributed diagnosis architecture assumes a decomposition of the process into subsystems, each with its corresponding LD, with similar functions and with possible communication between them. This communication must be properly designed; therefore, the local diagnoses are globally consistent. This architecture is shown in Figure 2.

![Distributed diagnosis architecture](image-url)

For the flotation process, in this paper we propose the design of the distributed system taking into account only the models of each subsystem to design LDs independently considering minimizing the communication between them until reaching the same diagnosis as with a centralized diagnosis. Let us consider the system $\Sigma$ and define the following:

A decomposition of the system $\Sigma(z,x,f)$, into several subsystems $\Sigma_i(z_i,x_i,f_i)$ is defined as a partition of its equations. Let $\Sigma(z,x,f) = \{\Sigma_1(z_1,x_1,f_1), ..., \Sigma_n(z_n,x_n,f_n)\}$ with $\Sigma_i(z_i,x_i,f_i) \subseteq \Sigma(z,x,f)$, $\bigcup_{i=1}^{n} \Sigma_i(z_i,x_i,f_i) = \Sigma$, $\Sigma_1(z_1,x_1,f_1) \neq \emptyset$ and $\Sigma_i(z_i,x_i,f_i) \cap \Sigma_j(z_j,x_j,f_j) = \emptyset$ if $i \neq j$. where $z_i$ is the vector of known variables in $\Sigma_i$, $x_i$ is the vector of unknown variables in $\Sigma_i$ and $f_i$ is the vector of faults in $\Sigma_i$. The set of variables and faults of the $i^{th}$ subsystem $\Sigma_i$, denoted as $X_i, Z_i$, and $F_i$ respectively, are defined as the subset of variables of $X$, $Z$, and $F$ respectively, that are involved in the subsystem $\Sigma_i(z_i,x_i,f_i)$ also denoted by $\Sigma_i$.

For the flotation process, we consider each level as a subsystem, therefore, the first subsystem includes a tank and the outlet pipe, the second to the fourth subsystems, contain 2 tanks, the pipe between them and the outlet pipe and the fifth subsystem includes a tank and the outlet pipe, see Table 1.

Table 1. Model decomposition of the flotation process system into subsystems $\Sigma_i(z_i,x_i,f_i)$, $i = 1, 2, 3, 4, 5$.

| $\Sigma_1$ | $F_1$ | $X_1$ | $Z_1$ | $\Sigma_2$ | $F_2$ | $X_2$ | $Z_2$ | $\Sigma_3$ | $F_3$ | $X_3$ | $Z_3$ | $\Sigma_4$ | $F_4$ | $X_4$ | $Z_4$ | $\Sigma_5$ | $F_5$ | $X_5$ | $Z_5$ |
|------------|-------|-------|-------|------------|-------|-------|-------|------------|-------|-------|-------|------------|-------|-------|-------|------------|-------|-------|-------|
| $\{e_1, e_2, e_3, e_4, e_5, e_6, e_7\}$ | $\{f_1, f_2\}$ | $\{x_1, x_2, x_3, x_4, x_5, x_6, x_7\}$ | $\{z_1, z_2, z_3, z_4, z_5, z_6, z_7\}$ | $\{e_8, e_9, ..., e_{10}\}$ | $\{f_3, f_4, f_5, f_6\}$ | $\{x_8, x_9, ..., x_{10}\}$ | $\{z_8, z_9, z_{10}\}$ | $\{e_{11}, e_{12}, ..., e_{17}\}$ | $\{f_7, f_8, f_9, f_{10}\}$ | $\{x_{11}, x_{12}, ..., x_{17}\}$ | $\{z_{11}, z_{12}, z_{13}\}$ | $\{e_{18}, e_{19}, ..., e_{36}\}$ | $\{f_{11}, f_{12}, f_{13}, f_{14}\}$ | $\{x_{18}, x_{19}, ..., x_{36}\}$ | $\{z_{18}, z_{19}, z_{20}\}$ | $\{e_{37}, e_{38}, ..., e_{40}\}$ | $\{f_{15}, f_{16}\}$ | $\{x_{37}, x_{38}, ..., x_{40}\}$ | $\{z_{37}, z_{38}, z_{39}\}$ |

The set of local variables of the $i^{th}$ subsystem, denoted by $X^i$, is defined as the subset of variables of $X_i$ that are only involved in the subsystem $\Sigma_i$.

Definition 10. (Shared variables). The set of shared variables of the $i^{th}$ subsystem, denoted as $X^s_i$, is defined as:

$$X^s_i = \bigcup_{j=1, j \neq i}^{n} (X_i \cap X_j) = X_i \setminus X^j_i$$

(1)

The set of shared variables of the whole system $\Sigma$ is denoted by $X^s$.

Without loss of generality, we consider that all known variables of $Z_i$ are local to the subsystem $\Sigma_i$, for $i = 1, \ldots, n$. If the same input was applied to several subsystems, it could be artificially replicated.

3.3 Distributed FMSO sets

Definition 11. (Local FMSO set). $\varphi$ is a local FMSO set of $\Sigma_i(z_i,x_i,f_i)$ if $\varphi$ is an MFSO set of $\Sigma(z,x,f)$ and if

[Diagram of distributed diagnosis architecture]
ϕ ⊆ Σi, Xϕ ⊆ Xi and Zϕ ⊆ Zl
i. The set of local FMSO
sets of Σi is denoted by Φl
i. The set of all local FMSO sets
is denoted by Φl
. The
set of all shared FMSO sets is denoted by Φs = Φl
i = ∅ (2)

No local FMSOs were found considering only informa-
tion from each subsystem. The shared FMSOs for each

Based on the number of shared variables and on the
optimization heuristic a root FMSO set makes use of an optimization heuristic
defined in P´erez-Zuniga et al. (2017)

Some properties required for the generation of compound
FMSO sets starting with ϕ
 are called a compound FMSO set.

The set of compound FMSO sets is denoted by Φc. The set of all compound FMSO
sets is denoted by Φc = Φi
i = 1

Definition 14. (Root FMSO set). If a compound FMSO set ϕ
 includes a shared FMSO set ϕ
 such that ϕ
 = 1, then the signature of a fault
includes all local FMSO sets; ϕ
 as root FMSO set: ϕ
 ← ϕ
;

Label ϕ
 as root FMSO set: ϕ
 ← ϕ
;

Let X
ϕ
 be the set of shared variables of ϕ
;

ϕ
→ Build a ‘good’ compound FMSO set
including ϕ* by always selecting the ‘best’
shared FMSOs to cover newly introduced
shared variables;

ϕ
 ← Φ
i
∪ Φ
i
;

Find a minimal cardinality set of local
FMSOs achieving the same diagnosability
as all local FMSO sets;

ϕ
 ← Φ
i
∪ Φ
i
;

end while
end for

4.2 On-line distributed operation of LDs

After the off-line design of the LDs performed with algo-
rithm 1, the online operation of the distributed diagnoser
relies on the bank of residual generators ARR
i,
selected for each LD LDi, i = 1, . . . , n, fed by measured signals
from their corresponding subsystems. As shown in Figure
3, fault isolation is carried out after fault detection using
local fault signature matrices according to Deﬁnition 17.

Definition 17. (FSM of a subsystem). Given a set ARR
i,
composed of n
i
 ARRs and Fi the set of considered n
i
 faults for the subsystem Σi and consider the function
ARR
i × Fi × ... 0, 1, then the signature of a fault f ∈ Fi is the binary vector FS
i(f) = [τ1, τ2, ..., τn]
T
, where
k = 1 if f is involved in the equations used to form
arr
k ∈ ARR
i,
otherwise τk = 0. The signatures of all
the faults in Fi together constitute the fault signature matrix (FSM) FSM
i
for subsystem Σi, i.e. FSM
i
= [FS
i(f1), ..., FS
i(fn)]
T
.

5. APPLICATION TO THE FLOTATION PROCESS

5.1 Offline distributed generation of LDs

In this section, the construction of the LD for each sub-
system is presented in order to diagnose all system faults.
Below the steps of the offline design:

1. - The local FMSOs are calculated for each of the sub-
systems, considering only local information.

\[ \Phi_1^l = \Phi_2^l = \Phi_3^l = \Phi_4^l = \Phi_5^l = \emptyset \]  (2)

No local FMSOs were found considering only information from each subsystem. The shared FMSOs for each
Algorithm 2. On-line Residual Operation of LDs.
1: for i=1...n do
2: For each LD:
3: Compute ARRs for LD_i
4: for j=1...m do
5: For all selected compound FMSO sets:
6: $ARR_{ij} \leftarrow$ Compute analytical residual
7: generators of LD_i;
8: Save the set of known variables of
9: each $ARR_{ij}$;
10: $Z_{LD_i} \leftarrow Z_{LD_i} \cup Z_{ARR_{ij}}$;
11: end for
12: By means of the fault signature matrix ($FSM_i$)
13: verify the isolability of faults of each subsystem;
14: end for
15: Add the known variables of the vector $Z_{LD_i}$ to the
16: fault diagnosis software for the online calculation of
the ARRs of the LDs;
17: Generate a on-line scalar signal $arr_{tk}$ from
the respective $ARR_{ij}$ using the signals of $Z_{LD_i}$.

subsystem are then determined by considering the vector
of shared variables ($X^s = \{x_2, x_4, x_6, x_8, q_1, q_3, q_5, q_7\}$) as
part of the vector of known variables for each subsystem.

2.- For subsystems $\sigma_1$ to $\sigma_5$, shared FMSO sets are
computed, Results are given in Table 3.

3.- For each subsystem, Algorithm 1 chooses from the set
of shared FMSO sets, a subset that is labeled as root
FMSO set and complete with a shared FMSO set each
of its shared variables until get a set of compound FMSO
sets that can diagnose all the faults of that subsystem.
The set of compound FMSO sets capable of detecting and
isolating the faults constitute the LD of the corresponding
subsystem. Results are given in Table 3.

5.2 On-line distributed residual operation of LDs

Using Algorithm 2, the ARRs are calculated and the
isolation of the 16 faults of this system is verified, as shown
in Table 4 to 8. As example, Figure 4 shows the ARRs
operating online for subsystem 1, as can be seen in the
case of a momentary fault of the tank level sensor 1 ($f_1$)
from 600 s. up to 650 s., there is a detection of $ARR_1$ and
no detection of $ARR_2$, which demonstrates the isolation
of this fault locally.

| $\Sigma_1$ | $\Phi_1^1 = \{\varphi_1,\varphi_2,\varphi_3\}$ |
|-----------|----------------------------------|
| $\varphi_1$ | $\{e_2, e_5, e_6\}$ |
| $\varphi_2$ | $\{e_1, e_3, e_4, e_5\}$ |

| $\Sigma_2$ | $\Phi_2^1 = \{\varphi_1,\varphi_2,\varphi_3\}$ |
|-----------|----------------------------------|
| $\varphi_1$ | $\{e_2, e_5, e_6, e_7, e_8, e_9, e_{10}, e_{11}\}$ |
| $\varphi_2$ | $\{e_1, e_{12}, e_{14}, e_{15}\}$ |
| $\varphi_3$ | $\{e_9, e_{11}, e_{12}, e_{13}, e_{14}\}$ |

| $\Sigma_3$ | $\Phi_3^1 = \{\varphi_1,\varphi_2,\varphi_3\}$ |
|-----------|----------------------------------|
| $\varphi_1$ | $\{e_2, e_5, e_6, e_7, e_8, e_9, e_{10}, e_{11}\}$ |
| $\varphi_2$ | $\{e_1, e_{12}, e_{14}, e_{15}\}$ |
| $\varphi_3$ | $\{e_9, e_{11}, e_{12}, e_{13}, e_{14}\}$ |

| $\Sigma_4$ | $\Phi_4^1 = \{\varphi_1,\varphi_2,\varphi_3\}$ |
|-----------|----------------------------------|
| $\varphi_1$ | $\{e_2, e_5, e_6, e_7, e_8, e_9, e_{10}, e_{11}, e_{12}\}$ |
| $\varphi_2$ | $\{e_1, e_{12}, e_{14}, e_{15}\}$ |
| $\varphi_3$ | $\{e_9, e_{11}, e_{12}, e_{13}, e_{14}, e_{15}\}$ |

| $\Sigma_5$ | $\Phi_5^1 = \{\varphi_1,\varphi_2\}$ |
|-----------|----------------------------------|
| $\varphi_1$ | $\{e_2, e_5, e_6, e_7, e_8, e_9, e_{10}, e_{11}, e_{12}, e_{13}, e_{14}\}$ |
| $\varphi_2$ | $\{e_1, e_{12}, e_{14}, e_{15}\}$ |

| $\varphi_3$ | $\{e_9, e_{11}, e_{12}, e_{13}, e_{14}, e_{15}\}$ |

| $\varphi_4$ | $\{e_2, e_5, e_6, e_7, e_8, e_9, e_{10}, e_{11}, e_{12}, e_{13}, e_{14}, e_{15}\}$ |

Table 2. Shared FMSO sets of $\Sigma_1$ to $\Sigma_5$.

| $\Sigma_1$ | $\Phi_1^2 = \{\varphi_4,\varphi_5,\varphi_6\}$ |
|-----------|----------------------------------|
| $\varphi_4$ | $\{e_2, e_5, e_6\}$ |
| $\varphi_5$ | $\{e_1, e_3, e_4, e_5\}$ |
| $\varphi_6$ | $\{e_1, e_2, e_3, e_4\}$ |

| $\Sigma_2$ | $\Phi_2^2 = \{\varphi_7\}$ |
|-----------|----------------------------------|
| $\varphi_7$ | $\{e_1, e_2, e_3, e_4\}$ |

| $\Sigma_3$ | $\Phi_3^2 = \{\varphi_8\}$ |
|-----------|----------------------------------|
| $\varphi_8$ | $\{e_1, e_2, e_3, e_4\}$ |

| $\Sigma_4$ | $\Phi_4^2 = \{\varphi_9\}$ |
|-----------|----------------------------------|
| $\varphi_9$ | $\{e_1, e_2, e_3, e_4\}$ |

| $\Sigma_5$ | $\Phi_5^2 = \{\varphi_{10}\}$ |
|-----------|----------------------------------|
| $\varphi_{10}$ | $\{e_1, e_2, e_3, e_4\}$ |

Table 3. Compound FMSO sets of $\Sigma_1$ to $\Sigma_5$.

| Faults | $f_1$ | $f_2$ |
|--------|-------|-------|
| $arr_1 \inARR_{R1}$ | X |  | X |
| $arr_2 \inARR_{R1}$ | X | X |

Table 4. Isolation capability for ARRs for $LD_1$.

| Faults | $f_1$ | $f_4$ | $f_6$ |
|--------|-------|-------|-------|
| $arr_3 \inARR_{R2}$ | X | X | X |
| $arr_4 \inARR_{R2}$ | X | X | X |

Table 5. Isolation capability for ARRs for $LD_2$.

| Faults | $f_7$ | $f_8$ | $f_{10}$ |
|--------|-------|-------|---------|
| $arr_5 \inARR_{R3}$ | X | X | X |
| $arr_6 \inARR_{R3}$ | X | X | X |

Table 6. Isolation capability for ARRs for $LD_3$.

Finally, Figure 5 shows the human machine interface of
the fault diagnosis software running on-line where a fault
alarm is shown in value 2 ($f_6$). This software is executed
Faults

\[
\begin{array}{c|cccc}
\text{arr}_7 & f_{11} & f_{12} & f_{13} & f_{14} \\
\text{arr}_8 & X & X & & \\
\end{array}
\]
\text{arr}_7 \in \text{ARR}_{4,1} \quad X \quad X
\text{arr}_8 \in \text{ARR}_{4,2} \quad X \quad X

Table 7. Isolation capability for ARRs for LD_{4}.

Faults

\[
\begin{array}{c|cc}
\text{arr}_{10} & f_{15} & f_{16} \\
\text{arr}_{10} & \in \text{ARR}_{5,1} & X \\
\text{arr}_{10} & \in \text{ARR}_{5,2} & X \\
\end{array}
\]

Table 8. Isolation capability for ARRs for LD_{5}.

Fig. 4. LD for subsystem 1

in a programmable automation controller (PAC) that receives the signals from the sensors and generates the control signals.

Fig. 5. Fault diagnosis software

In fact, the proposed approach is applicable to fault diagnosis of a large floating circuit, decomposing the latter into subsystems. Here, as shown above, each subsystem in the distributed architecture will have its own LD.

6. CONCLUSION

An approach for on-line fault diagnosis in a flotation process was proposed based on a distributed architecture. The application of the approach allows the development of diagnosis systems for large-scale flotation circuits. The fault diagnosis system developed, was tested by simulation validating that the 16 faults can be detected and isolated locally or at a higher level. Likewise, a procedure for residual generation was presented and it has been tested into a programmable automation controller for on-line operation of fault diagnosis software.

7. ACKNOWLEDGMENTS

This work was funded by Proyecto de Mejoramiento y Ampliación de los Servicios del Sistema Nacional de Ciencia Tecnología e Innovación Tecnológica’ 8682-PE, Banco Mundial, CONCYTEC and FONDECYT through grant N48-2018-FONDECYT-BM-IADT-MU.

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