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Operating mode recognition. Application to a grinding mill process.

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Abstract— **Process monitoring needs the development of data analysis tools aiming at recognizing, at each time instant, system operating mode using the measurement collected on the system. This communication aims at presenting a method relying on measurement analysis, able to identify operating modes without the knowledge of the mathematical models describing these modes. The proposed method relies on the writing of a *global* model combining, in a multiplicative way, the models describing the different modes. The parameters of this global model are then numerically identified from the available set of measurements. The sensitivity analysis of the global model with regard the input/output variables then provides an indicator to identify, at each instant, the current operating mode. The proposed method is applied on a simplified model of a grinding mill.**

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I. Introduction

The complexity of technological as well environmental processes renders their management more and more difficult. This complexity comes from the involved phenomena and their numerous interactions, the dimension of the concerned processes but also because it is desirable to optimize their functioning. Process supervision methods therefore become more and more sophisticated and, during the last two decades, process diagnosis has become a discipline in its own.

A. Motivations

The difficulty of implementing monitoring of a process is highly related to the nature of the changes it undergoes over time. We distinguish on the one hand, the modifications imposed by the operator depending on the production requirements (for example modification of the process set points) and, on the other hand, unwanted changes usually due to the environment of process (not or hardly predictable disturbances). The first changes being perfectly mastered, the second type of change is the need to detect very early, in order to propose actions that can eliminate or minimize the adverse effects of these disturbances.

B. Definitions

Disturbances that affect the behavior of a system can also affect its actuators, its sensors or the components constituting the system itself. Understandably, when the diagnostic operation is not only to detect a change in behavior, but also to determine or locate the affected elements, this step being known under the term fault isolation. This step is usually completed, if possible, by a fault characterization that is to say by an estimate of the amplitude. Based on this magnitude, reflecting the severity of the fault, the control law to counteract the influence of this failure will be defined.

Monitoring can also be done from the knowledge of the different operating modes of the system. Generally, a system is characterized by a nominal operating mode corresponding to normal operation mode. When knowledge of the system is sufficient and when the quality of historical data permits, it is common to have other information characterizing normal and abnormal operating modes. In this case, monitoring, so-called supervised mode, is to detect as quickly as possible the eventual transition from one mode to another, then consider compensatory actions to be taken to restore functioning in the nominal mode.

There are however more difficult situations where different modes of operation have not yet been characterized. In this case, monitoring will be carried out in unsupervised mode. The only information available is the measurements of the system during operation; the latter must contain sufficient information to discern the operating modes even if they were not a priori characterized. In the remainder of this communication, it is this situation that will be exposed.

C. Historic elements

Detecting change of operation modes has been the subject of numerous studies in the field of signal processing. The first of these studies have focused on determining average jumps in signals [11], these jumps are themselves images of changes in a system. These techniques were then generalized to the phase jump detection, variance and frequency [15] and also in estimating regime change time instants [20] [21] [9].

This detection is directly applied to the signals from the sensors, but often detected jumps are not attributable to sensors but changes are the result of system behavior modifications. For this reason, these skip detection techniques must be applied to signals reflecting system behavior changes, such as the signal generated by the innovation sequence of the Kalman filter [16] which is of particular structure. This gave rise to many developments on the construction of indicators suitable for burnout detection. In particular, these indicators have been structured so as to locate and isolate faults and operating modes. Note that most of these techniques rely on the use of models that characterize the normal operation of the systems and more rarely the malfunction situations. In

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addition, some techniques have been developed also in the absence of a model describing the operation of the systems, especially using the principal component analysis techniques [13] to the linear case [2], [3], and their extensions known of kernel methods in the nonlinear case [14], [19].

The problem becomes more difficult when the event responsible for the mode change is not known. Indeed, for this unsupervised classification problem, if the different models are unknown, it is necessary to estimate simultaneously model parameters and data partitioning in order to associate to each model data that will allow its identification. As regards the application domain, the detection of regime change is the subject of many studies and this in a variety of fields, such as economics and finance, traffic and epidemics, image analysis, to name a few. The motivation for this interest probably lies in the issues related to the ability to detect as early as possible the change of mode of operation, so as to provide appropriate control strategies. However, little work on production systems or more generally technological systems have been published. Nevertheless include [10] for the detection of regime change operation of aircraft engines (due to the onset of mechanical vibrations), [12] for monitoring flight trajectories using a hybrid representation of their behavior, [25] in mining engineering, [4] in metallurgical engineering and [7] for a chemical process supervision.

The field of environmental monitoring is also the subject of many applications. In [8], the authors compare two probabilistic strategies to detect changes in the regime of a river. In [18] and [23], the application relates to the detection of regime change in marine ecosystems.

In all these applications, it is noted that it is necessary to know the models characterizing different operating system. This is to be compared with the proposed method in which these models are not required. Conversely, a single model, resulting in a certain multiplicative form all operating regimes, is constructed without knowing the parameters of each operating mode. The main contribution of the proposed method is to detect mode changes without knowing the model parameters characterizing each mode. The number of operating modes (described by so-called local models) as well as the model structures describing each of these modes are known a priori. The method relies on the estimation of the parameters of a "global" model of the system, resulting from a multiplicative combination of local models. The sensitivity analysis of the global model with regard the input/output variables then provides an indicator to detect changes in the operating mode.

D. Hypotheses

As previously mentioned, the proposed mode recognition method doesn't need *a priori* the knowledge of the models describing these modes.

In the sequel, the following assumptions are assumed:

- The number of operating modes is *a priori* known and limited to 2;
- The input/output models describing each operating modes are linear in their variables;
- A set of measurements collected on the system assumed to operate according to all its potential operating modes (here the two modes) is available;
- The inputs of the system are sufficiently persistent to allow the identification of its behaviour.

II. Main goal of the proposed method

The main goal of the proposed method is to detect the change of operating mode of a system based on the analysis of the measurements of its different input/output variables. The proposed method relies on the writing of a *global* model combining in a multiplicative way the models describing the different modes. The parameters of this global model are then numerically identified from the available set of measurements. The sensitivity analysis of the global model with regard the input/output variables then provides an indicator to identify, at each instant, the current operating mode. Subsection A uses a very simple model allowing to give the principle of the method.

A. System with two input variables

1) Local and global models: Let us denote y the output variable and x_1, x_2 the two input variables. The models describing, at the discrete time instant k, the two considered operating modes are written as:

$$\begin{cases} \text{Mode } M_1 & : \quad y_k + b_1\, x_{1,k} + a_1\, x_{2,k} = 0 \\ \text{Mode } M_2 & : \quad y_k + b_2\, x_{1,k} + a_2\, x_{2,k} = 0 \end{cases} \tag{1}$$

Depending on the operating conditions, the system behaviour is described at a particular time instant k by one of the two models M_1 or M_2. From the knowledge, at instant k, of the measurement triple $y_k, x_{1,k}, x_{2,k}$, it is desirable to identify the operating mode of the system. As the parameters a_i and b_i of these models are not know, a matching test of the measurement triple to M_1 or M_2 is not possible. Contrarily, this triple necessary verifies the global model defined by the following multiplicative form:

$$(y_k + b_1\, x_{1,k} + a_1\, x_{2,k})(y_k + b_2\, x_{1,k} + a_2\, x_{2,k}) = 0 \tag{2}$$

that can be also written as:

$$\begin{aligned} & p_0\, y_k^2 + p_1\, y_k\, x_{1,k} + p_2\, x_{1,k}^2 + p_3\, y_k\, x_{2,k} + \\ & p_4\, x_{1,k}\, x_{2,k} + p_5\, x_{2,k}^2 = 0 \end{aligned} \tag{3}$$

where the parameter p_0 can be arbitrarily chose equal to 1.

Remark 1: The equations (2) and (3) can be compared in order to establish the relations between the local model parameters a_i, b_i and the global ones p_i. In certain cases, depending on some rank conditions, local model parameters can be expressed from global ones. However, in that communication, the persued objective is restricted to the identification of the current operating mode without providing the model describing each mode (at least without searching to estimate explicitly the local model parameters).

With the following definitions:

$$\begin{aligned} z_k &= \begin{bmatrix} y_k & x_{1,k} & x_{2,k} \end{bmatrix}^T \\ R_2 &= \frac{1}{2} \begin{bmatrix} 2p_0 & p_1 & p_3 \\ p_1 & 2p_2 & p_4 \\ p_3 & p_4 & 2p_5 \end{bmatrix} \end{aligned} \tag{4}$$

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