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A variant of the particle swarm optimization for the improvement of fault diagnosis in industrial systems via faults estimation

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ABSTRACT

This paper proposes an approach for Fault Diagnosis and Isolation (FDI) on industrial systems via faults estimation. FDI is presented as an optimization problem and it is solved with Particle Swarm Optimization (PSO) and Ant Colony Optimization (ACO) algorithms. Also, is presented a study of the influence of some parameters from PSO and ACO in the desirable characteristics of FDI, i.e. robustness and sensitivity. As a consequence, the Particle Swarm Optimization with Memory (PSO-M) algorithm, a new variant of PSO was developed. PSO-M has the objective of reducing the number of iterations/generations that PSO needs to execute in order to provide a reasonable quality diagnosis. The proposed approach is tested using simulated data from a DC Motor benchmark. The results and analysis indicate the suitability of the approach as well as the PSO-M algorithm.

1. Introduction

A fault is an unpermitted deviation of at least one characteristic property or parameter of a system from the acceptable, usual or standard operating condition (Simani et al., 2002).

Faults can cause economic losses as well as damage to human capital and the environment. There is an increasing interest on the development of new methods for fault detection and isolation, FDI, also known as Fault Diagnosis, in relation to reliability, safety and efficiency (Isermann, 2005).

The FDI methods are responsible for detecting, isolating and establishing the causes of the faults affecting the system. They should also guarantee the fast detection of incipient faults (sensitivity to faults) and the rejection of false alarms that are attributable to disturbances or spurious signals (robustness).

The FDI methods are broken down into three general groups, the process history based methods (Venkatasubramanian et al., 2002c), those based on qualitative models (Venkatasubramanian et al., 2002b), and the quantitative model based methods, also known as analytical methods (Venkatasubramanian et al., 2002a).

The quantitative model based methods make use of an analytical or computational model of the system. The great variety of the proposed model based methods is brought down to a few basic concepts such as: the parity space; observer approach and the parameters identification or estimation approach (Isermann, 1984; Frank, 1990, 1996; Isermann, 2005).

Many papers and books have been devoted to making descriptions and establishing links among the different approaches for model based diagnosis (Frank, 1990; Venkatasubramanian et al., 2002a; Simani et al., 2002; Witczak, 2007; Metenidin et al., 2011). A clear description of each approach and their limitations are presented in Witczak (2007). In Witczak (2007) and Metenidin et al. (2011) it is recognized that observers and parity space approaches do not always allow the isolation of the actuators faults. For nonlinear models, the complexity on the observer design increases, while an exact model of the system is necessary for the parity space approach (Witczak, 2007; Metenidin et al., 2011).

Parameter estimation approach requires the knowing of the relationships between such parameters and the physical coefficients of the system, as well as the influence of the faults in these coefficients (Frank, 1990, 1996; Isermann, 2005). This approach does not provide a good diagnosis for the case of sensor faults. Furthermore, this usually demands a high computing time, which makes it infeasible for most situations (Isermann, 2005; Witczak, 2007).

The topics of robustness and sensitivity are of high interest in FDI. Thus, many robust analytical methods have been developed (Isermann, 1984, 2005; Frank, 1990; Chen and Patton, 1999; Patton et al., 2000). However, the unavoidable process disturbances and the modelling errors make that most FDI methods become unfeasible in practical applications (Simani et al., 2002; Simani and Patton, 2008). Therefore, further research on the topic of

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robust and sensitive FDI methods is indispensable (Isermann, 1984; Simani et al., 2002; Simani and Patton, 2008).

The FDI methods based in observers or parity space demand large efforts to generate robust and sensitive residuals, related to the fault detection. The generation of a residual is highly dependent on the model that describes the system.

This paper proposes an approach for FDI in industrial systems via faults estimation. The proposal allows to diagnose the system based on a direct fault estimation. Soft computing techniques are recognized as attractive tools for solving various problems related to modern FDI (Witczak, 2007; Metenidin et al., 2011). This approach considers the use of meta heuristics, in order to obtain a robust and sensitive diagnosis. Some FDI methods that use meta heuristics are reported in Witczak (2007), Yang et al. (2007), Wang et al. (2008) and Camps-Echevarría et al. (2010) and Metenidin et al. (2011).

The meta heuristics Particle Swarm Optimization (PSO) and Ant Colony Optimization (ACO) have simple structures. Moreover, they were recently applied to FDI (Liu et al., 2008; Liu, 2009; Samanta and Nataraj, 2009; Duarte and Quiroga, 2010; Metenidin et al., 2011). Therefore, they were selected for this approach.

This work is also aimed at studying the influence of parameters from PSO and ACO in robustness and sensitivity. This study is the basis for the development of a new variant of PSO, named Particle Swarm Optimization with Memory (PSO-M). The new algorithm has the objective of reducing the number of iterations/generations that PSO needs to execute, in order to discover reasonable quality solutions. This means less computational time, which allows faster diagnosis. PSO-M can be easily extended to other optimization problems.

The proposed approach also permits the direct estimation of the faults, indistinctly if they take place in the actuator, process or sensors. This estimation is based on the residual, which is directly obtained between the measurements of the output of the system and the output that estimates the model. This avoids restrictions to the nature of the model.

The main contributions of this paper can be summarized as follows: the study of a new approach for the development of robust and sensitive FDI methods based on direct fault estimation with the meta heuristics PSO and ACO; the study of the influence of their parameters in order to increase the robustness and sensitivity; and the development of a new variant PSO-M, which uses a pheromone matrix from ACO for storing the history of PSO, useful for improving the computational cost that is required by PSO. The viability of the proposal is demonstrated by diagnosing the simulation data from a DC Motor.

This paper is organized as follows. The second section introduces the modelling of faults and the model-based FDI methods via parameters estimation. The proposed approach for FDI is also described in this section. The third and fourth sections give a brief description of the algorithm for PSO and the algorithm for ACO, respectively. The fifth section justifies and describes the PSO-M algorithm. Afterward, the next section details the DC motor case study and its simulations. The other sections present the experimental methodology, experiments and results, following the same order. The tenth section presents a comparison between Parity Space, Diagnostic Observers and our proposal for FDI. Finally, some concluding comments and remarks are presented.

2. Modelling faults and FDI based on direct fault estimation

FDI based on model parameters, which are partially unknown, requires online parameters estimation methods. For that purpose the input vector $u(t) \in \mathbb{R}^m$, the output vector $y(t) \in \mathbb{R}^p$ and the basic model structure must be known (Isermann, 2005).

The models for describing the systems depend on the dynamics of the process and the objective to be reached with the simulation. The most used model is the linear time invariant (LTI), which has two representations: the transfer function or transfer matrix, and the state space representation. This last representation is also valid for non-linear models.

Let us express the input/output behavior of SISO (single input single output) processes by means of ordinary linear differential equations

$$y(t) = \psi^T(t)\Theta(t) \tag{1}$$

where

$$\Theta(t) = [a_1 \dots a_n \;\; b_0 \dots b_m] \tag{2}$$

and

$$\psi^T(t) = [-y^1(t) \dots -y^n(t) \;\; -u^1(t) \dots -u^m(t)] \tag{3}$$

where $y^n(t)$ and $u^m(t)$ indicate derivatives $(y^n(t) = dy^n(t)/dt^n)$.

The respective transfer function becomes, through Laplace transformation:

$$G_p = \frac{y(s)}{u(s)} = \frac{B(s)}{A(s)} = \frac{b_0 + b_1 s + \dots + b_m s^m}{1 + a_1 s + \dots + a_n s^n} \tag{4}$$

The faults affecting the system may eventually change one or several parameters in the vector $\Theta(t)$. The FDI based on model parameters is divided into two steps. The first is meant for the estimation of the model parameters vector $\Theta(t)$. The second for detecting and isolating the faults based on known relationships between model parameters, physical coefficients of the system and faults (Isermann, 1984, 2005).

The main drawback of this approach is that the model parameters should have physical meaning, i.e., they should correspond with the parameters of the system. In such situations, the detection and isolation of faults are very straightforward. Otherwise, it is usually difficult to distinguish a fault from a change in the parameters vector $\Theta(t)$. Moreover, the process of fault isolation may become extremely difficult because model parameters do not uniquely correspond with those of the system. It should also be pointed out that the detection of faults in sensors and actuators is possible but rather complicated (Witczak, 2007; Metenidin et al., 2011).

The two approaches that are commonly used for estimating the model parameters $\Theta(t)$ are classified with respect to the minimization function they use (Frank, 1990; Isermann, 2005):

- sum of least squares of the equation error;
- sum of least squares of output error.

The FDI based on parameters estimation considering the minimization of the sum of least squares of the output error requires numerical optimization methods. These methods give more precise parameters estimations but the computational effort is bigger, and on-line applications are, in general, not possible (Isermann, 2005). Another typical limitation regarding parameters estimation-based approaches is related to the fact that the input signal should be persistently excited (Witczak, 2007; Metenidin et al., 2011).

Instead of estimating the model parameters vector Θ, let us consider explicitly the faults in a SISO system in a closed loop described by a LTI model as

$$\begin{aligned} y(s) &= G_{yw}(s)w(s) + G_{yf_u}(s)f_u(s) \\ &\quad + G_{yf_y}(s)f_y(s) + G_{yf_p}(s)f_p(s) \end{aligned} \tag{5}$$

where $w(s) \in \mathbb{R}$ is the reference signal of the control system, f_u, f_p, $f_y \in \mathbb{R}$ are faults in the actuator, process and output sensors, respectively. The transfer function $G_{yw}(s)$ represents the dynamics of the system while $G_{yf_u}(s)$, $G_{yf_p}(s)$ and G_{yf_y} are the transfer