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Adaptive soft-sensors for on-line particle size estimation in wet grinding circuits☆

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Abstract

On-line particle size soft-sensors play an important role in the efficient operation of control systems in many industrial grinding plants. To cope with disturbances and changing operating points it will be necessary to adapt the soft-sensor parameters to the new conditions. This work proposes the use of constrained parameter estimation algorithms, in order to take into account some process prior knowledge and enhance the performance of the soft-sensor. Several experiments, using data taken from an industrial grinding circuit, illustrate the benefits of the proposed approach.

Keywords: Constrained parameter identification; Recursive least squares; Soft-sensors; Particle size distribution

1. Introduction

The profitable operation of grinding circuits depends mainly on a good measurement of the particle size distribution at the output stream. Unfortunately, this measurement in many industrial installations is not available all the time, since the sensor requires constant cleaning and it may be taken out of service for maintenance or calibration. Under these situations, it is convenient to have an estimate of the missing variable. Soft-sensors are based on the available information provided by other sensors, which can be correlated with the missing measurement. In this case, the knowledge concerning the relationship between the variables can be used to build a model, and the data available from the process can be used to get the necessary information to estimate the parameters of the soft-sensor model. Successful applications of soft-sensor technologies can be found in wide range of industries such as: petrochemical (Fortuna, Graziani, & Xibilia, 2005), pulp and paper (Dufour, Bhartiya, Dhurjati, & Doyle III, 2005), biotechnological (De Assis & Filho, 2000; Karakuzu, Türker, & Öztürk, 2006) and mineral processing (Casali et al., 1998; Gonzalez, Orchard, Cerda, Casali, & Vallebuona, 2003).

Many authors have proposed the use of non-linear autoregressive moving average with exogenous variables (NARMAX) type of models as on-line particle size estimators (Du, del Villar, & Thibault, 1997; Casali et al., 1998). The parameters of these models can be adapted using the data available while the real sensor is in operation.

There is often known model information in terms of the parameters, but this is ignored, since this type of information does not fit easily into the most popular identification algorithms (Chia, Chow, & Chizeck, 1991). Constraints on the allowable values of the parameters, which may be based on physical considerations or some known basic dynamical characteristics of the model, like for instance a stable one, are often not considered.

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On-line estimate of the parameters can be very useful when the system changes operational conditions. However, during transients the estimates can deviate to regions which violate some physical or logical motivated constraints. In this paper, two constrained parameter estimation methods are applied to the problem of on-line estimation of soft-sensor parameters.

This paper is organized as follows: Section 2 describes the structure of the model used as soft-sensor. Section 3 describes two algorithms for on-line parameters estimation. In Section 4, some experimental results, obtained with data from an industrial grinding circuit, illustrate their main characteristics. Finally, in Section 5 some conclusions are given.

2. Model structures for soft-sensors

NARMAX models represent a popular soft-sensor structure, which basically has a linear autoregressive part and a series of nonlinear terms, considering the measured variables, as shown in the following expression:

$$\hat{y}(t) = \sum_{j=1}^{n} \alpha_j y(t-j) + \sum_{j=1}^{l} \beta_j \psi_j(\mathbf{x}(t), \ldots, \mathbf{x}(t-m)) + \gamma, \quad (1)$$

where α_j represent the autoregressive parameters, β_j the parameters associated to the regressor $\mathbf{x}(t) = [x_1(t), \ldots, x_l(t)]$ and γ a bias term. The integer n and m represent the number of delayed outputs and inputs necessary to approximate the system. The nonlinear functions ψ_j can be selected by some physically motivated reasons (Casali et al., 1998) or as general nonlinear functions, like Fuzzy sets (Gonzalez et al., 2003).

In this work; however, a simpler model described by the following equation is proposed

$$\hat{y}(t) = \sum_{j=1}^{l} \beta_j h_j(t) * x_j(t) + \gamma, \quad (2)$$

where the operator "$*$" represents convolution, $x_j(t)$ are the measured variables, $h_j(t)$ are the impulse responses of stable linear filters, β_j and γ are the parameters to be estimated. The main advantage of this model is that different inputs can have different dynamical effects on the estimated variable. This is a very useful feature when the measured variables are taken from different locations in the process, where some of them can be located far away from the measurement to be estimated. Notice that this representation can be considered a special case of a more general model, known as Wiener model. In this paper, h_j are assumed to be known, though the full identification of this class of model can be carried out by subspace identification algorithms (Lovera, Gustafsson, & Verhaegen, 2000).

3. Adaptive algorithms

In this section, the algorithms associated to the estimation of the soft-sensor parameters are summarized. The models described in Section 2 can be written in a compact form as

$$\hat{y}(t) = \hat{\theta}' \phi(t-1), \quad (3)$$

where θ represents the vector of parameters and ϕ the vector of functions, having as arguments the measured variables. For instance, Eq. (2) can be represented by (3) with $\hat{\theta}' = [\beta_1, \beta_2 \ldots \beta_l, \gamma]$ and $\phi(t) = [h_1(t) * x_1(t), h_2(t) * x_2(t)..h_l(t) * x_l(t), 1]'$.

A simple closed convex region in the parameter space is considered. This region is defined as

$$\mathscr{C} = \{\theta \,\varepsilon\, \mathbb{R}^p : \overline{\theta}_i \geqslant \theta_i \geqslant \underline{\theta}_i, \forall i = \overline{1,p}\}, \quad (4)$$

where $\theta = [\theta_1, \ldots, \theta_p]'$ is the vector parameter, $\overline{\theta}_i$ and $\underline{\theta}_i$ are upper and lower ith parameter bound, respectively.

In many industrial plants, soft-sensors must be programmed in computers with limited computational resources. Therefore, it is interesting to compare the performance of algorithms with different degrees of complexity.

3.1. Error projection (EP) algorithm

The EP algorithm updates the parameters, according to the following equation:

$$\hat{\theta}^u(t+1) = \hat{\theta}(t) + \eta \frac{\phi(t-1)(y(t) - \hat{\theta}(t)'\phi(t-1))}{1 + \phi(t-1)'\phi(t-1)}, \quad (5)$$

where $0 < \eta < 2$ is a constant. The subscript "u" signifies that the estimated parameters are unconstrained solutions. This algorithm results from the following optimization problem. Given $\hat{\theta}(t)$ and $y(t)$ determine $\hat{\theta}(t+1)$ so that

$$J = \tfrac{1}{2}\|\hat{\theta}(t+1) - \hat{\theta}(t)\|^2, \quad (6)$$

is minimized subject to $y(t) - \hat{\theta}(t)'\phi(t-1) = 0$.

If the algorithm leads to some estimated values outside the convex region $\mathscr{C}$ (constrained region), one must simply project these estimates orthogonally onto the surface of the region before continuing. In this case the constrained algorithm saturates the estimated values of the parameters in their limits (Goodwin & Sin, 1984); i.e.

$$\hat{\theta}_i(t+1) = \begin{cases} \overline{\theta}_i, & \hat{\theta}_i^u(t+1) > \overline{\theta}_i, \\ \hat{\theta}_i^u(t+1), & \underline{\theta}_i \leqslant \hat{\theta}_i^u(t+1) \leqslant \overline{\theta}_i, \\ \underline{\theta}_i, & \hat{\theta}_i^u(t+1) < \underline{\theta}_i \end{cases} \quad (7)$$

$\forall i = \overline{1,p}$.