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Soft Sensing of Overflow Particle Size Distributions in Hydrocyclones Using a Combined Method*

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Abstract: Precise, real-time measurements of overflow particle size distributions in hydrocyclones are necessary for accurate control of the comminution circuits. Soft sensing measurements provide real-time, flexible, and low-cost measurements appropriate for the overflow particle size distributions in hydrocyclones. Three soft sensing methods were investigated for measuring the overflow particle size distributions in hydrocyclones. Simulations show that these methods have various advantages and disadvantages. Optimal Bayesian estimation fusion was then used to combine three methods with the fusion parameters determined according to the performance of each method with validation samples. The combined method compensates for the disadvantages of each method for more precise measurements. Simulations using real operating data show that the absolute root mean square measurement error of the combined method was always about 2% and the method provides the necessary accuracy for beneficiation plants.

Key words: soft sensing; overflow particle size distribution; machine learning; identification

Introduction

A hydrocyclone is an efficient piece of equipment for separating particle mixtures by size, so they are widely applied in the beneficiation field, where the overflow particle size distribution in hydrocyclones is of great significance. Each kind of ore has a best particle size for smelting, with smaller particles result in losses in the floatation process and wasted power in the ball mills while larger particles have reduced recovery rates which results in difficulty in subsequent processes. Therefore, the overflow particle size distributions in hydrocyclones should be accurately measured to efficiently control the ball mills and hydrocyclones and to avoid over or under milling. Accurate measurements will significantly improve production quality and recovery rate while reducing energy consumption.

Normally, the overflow particle size distributions in hydrocyclones is evaluated by the proportion of particles within a certain size range. This paper concentrates on particles smaller than 74 μm , with the proportion of particles within this range denoted as β_{-74} as a decimal between 0 and 1.

Off-line manual tests have been widely used to measure the overflow particle size distributions in hydrocyclones because they are easy to realize and precise, but the intervals between tests are normally too long (normally several hours), so the results cannot be used for real-time feedback to a controller. Online measurements using particle size measuring instruments can provide real-time measurements, but the instruments are quite expensive and require complex maintenance. Many plants cannot afford such equipment. Soft sensing monitors measure non-measurable or hard-to-measure variables by measuring more easily measured variables which are then related to the

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difficult variables. Soft sensing can provide real-time measurements with equipment and maintenance costs that are relatively low and soft sensors can be easily modified. Therefore, soft sensing methods are more appropriate for measuring the overflow particle size distributions in hydrocyclones.

There are several kinds of soft sensing methods[1], for measuring the overflow particle size distributions in hydrocyclones. Machine learning methods analyze the hydrocyclone as a nonlinear mapping problem with the mapping developed using training data. This method does not require a physically-based model, but the resulting model lacks physical meaning. The method over-emphasizes the training samples and cannot guarantee the measuring reliability outside the range of the training samples. In addition, the training process may fail and result in a wrong model if poor training samples are used and “good” and “poor” training samples cannot be easily distinguished beforehand. The following soft sensing methods for hydrocyclones are proposed: soft sensors for measuring the reduced cut size $d_{50\mathrm{c}}$ based on fuzzy and neural-fuzzy methods[2-4] and for the overflow particle size distributions in hydrocyclones based on support vector machines[5]. Identification methods combine several theoretical and empirical formulas to deduce a simplified hydrocyclone model, with a training sample based identification method then used to estimate the non-measurable parameters in the model. The measurements are then based on these estimated parameters. All the variables and parameters in this method possess some physical meaning; therefore, this method can be easily modified and improved by new theories. This method is not as sensitive to the training samples as the machine learning methods. The most serious disadvantage of the identification methods is that, because many hydrocyclone formulas are empirical or semi-empirical, the combined measurement model is not as accurate. Casali et al.[6] described a soft sensor identification method for measuring overflows concentration, but there are no known reports using the identification method to measure the overflow particle size distributions in hydrocyclones. Arterburn[7] used an empirical formula in table form, this formula can be directly utilized for soft sensor measurements. The main advantage of this method is that it does not need training samples and is easy to implement, but the measuring precision will be poor if the operating conditions change.

This paper combines these methods and presents a simulation based on real operating data from a beneficiation plant to validate the performance of each individual method and the combined method.

1 Support Vector Machine Method

The support vector machine (SVM) method is a general machine learning method derived from pattern recognition theory and statistical learning theory. The resulting learning machine minimizes both the empirical risk and the upper bound of the Vapnik-Chervonenkis (VC)-dimension, which implies that it accurately fits the training samples and possesses good generalization ability. The SVM method has been applied to pattern recognition, function regression, and probability density function estimation. This model uses the SVM method for function regression[8] .

Unlike neural networks, the SVM method does not exactly fit the training sample but fits the training samples within a predefined error tolerance with penalties for training samples outside the tolerance, which are usually a small fraction of the total. The regression function should be made as smooth as it can be so that the SVM can be generalized even if only several training samples are available. Therefore, the SVM method is a reasonable method for problems with relatively few training samples.

Assume there are l training samples $(\boldsymbol{x}_i, y_i)$, $i=1,2,\ldots,l$ that obey an unknown function with additive observation noise:

$$y_i = f_{\mathrm{real}}(\boldsymbol{x}_i)+\upsilon_i,\ \ i=1,2,\ldots,l \tag{1}$$

where υ_i, $i=1,2,\ldots,l$ are i.i.d. observation noises. The regression functions for the SVM are of the form:

$$f(\boldsymbol{x})=\sum_{i=1}^{l}(\alpha_i-\alpha_i^*)K(\boldsymbol{x},\boldsymbol{x}_i)+b \tag{2}$$

where $\boldsymbol{x}_i$, $i=1,2,\ldots,l$ denote the input variables in the training samples which may be scalars or vectors; l denotes the number of training samples; α_i, α_i^*, and b are parameters which must be determined by the training; and K is a kernel function whose form must be determined beforehand.

The SVM training process determines α_i, α_i^*, and b by solving a convex optimization problem:

$$\max J=-\frac{1}{2}\sum_{i=1}^{l}\sum_{j=1}^{l}(\alpha_i-\alpha_i^*)(\alpha_j-\alpha_j^*)K(\boldsymbol{x}_i,\boldsymbol{x}_j)-\varepsilon\sum_{i=1}^{l}(\alpha_i+\alpha_i^*)+\sum_{i=1}^{l}y_i(\alpha_i-\alpha_i^*) \tag{3}$$