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Online Estimation of the pH Value for Froth Flotation of Bauxite Based on Adaptive Multiple Neural Networks *

Xiao-li Wang*, Lei Huang*, Peng Yang*, Chun-hua Yang*, Qi-yue Xie**

**School of Information Science and Engineering, Central South University, Changsha 410083, China*
(e-mail: xlwang@ csu.edu.cn; 447994439@qq.com; csuyangpeng@gmail.com; ychh@csu.edu.cn).
***School of Energy and Power Engineering, Changsha University of Science and Technology, Changsha 410076, China*
(e-mail:qyxie168@163.com)

Abstract: pH value is an essential factor in the control of froth flotation process. However, it cannot be measured online because the online-pH detector is easily damaged due to the poor field conditions, and maintenance is always delayed. Therefore, considering of the characteristics that the pH value fluctuate around a prescribed value due to the variation of the operating conditions when the ore is stable, and the prescribed control range of pH value changes when the ore type changes, multiple RBF networks based on sample classification and adaptive retraining strategy are proposed corresponding to these two characteristics for the online estimation of the pH value. Simulation results using the industrial data collected in a flotation process of bauxite show that an improvement in predictive accuracy and fitting capability can be achieved by adaptive multiple neural networks (Adaptive MNN) (RMSE=0.0957, R^2=0.6503) in comparison with the MNN (RMSE=0.1591, R^2=0.2312) and the single RBF neural network model (RMSE=0.2023 , R^2= 0.1930).

Keywords: Froth flotation, pH value, online estimation, multiple networks, adaptive retraining.

1. INTRODUCTION

Froth flotation is a method for mineral separation based on the physicochemical and surface chemistry of the constituent minerals, where regents (frother, collector, etc.) are added and air is sparged to produce froth and to adjust the surface hydrophobicity of the particles with different minerals so that particles with valuable minerals can adhere to the froth and be collected, while the other particles with mainly uninterested minerals are eliminated through the tailings. The acidity (pH value) of the slurry is an essential factor in the controlling of the process [Somasundaran and Nagaraj, 1984], which directly influences the dissociation of the regents and therefore the surface hydrophobicity of the particles. However, online measurement equipment for pH value does not work well in most of the flotation plants in China because it is easy to be adhered by the slurry and breakdown, and maintenance is usually not in time. So, offline measurement is still used in these flotation plants, and control of the pH value is time delayed. To solve this problem, online soft sensing is an effective way.

Neural network is commonly used for soft-sensing or prediction modeling [e.g. Sandra et al., 2016; Seng et al., 2008; Yang et al., 2013] because of its strong fitting ability to nonlinear systems. For froth flotation process, Jahedsaravani et al.[2014] models the relationship between the froth image variables (as inputs) and the flotation performances (as outputs) of a laboratory batch flotation process using neural networks. However, for data-driven modeling like neural networks, model mismatching problems usually occur, especially for long-time running, because the feed properties and disturbances vary constantly and therefore operating conditions vary, and the process data is with noise. So, multiple (neural network) models [e.g. Cho et al. 1997; Ahmad and Jie, 2005; Piuleac et al., 2010, Domlan et al., 2011; Cao et al., 2013.] are established to deal with different operating conditions. Ahmad and Jie [2005] uses data fusion techniques to combine multiple neural networks to improve the robustness of the model in nonlinear process modeling. Piuleac et al. [2010] proposes a modeling method based on stacked neural networks which has different hidden layers and hidden nodes. Cho et al.[1997] uses two neural networks for prediction and proves that model accuracy and reliability are improved. Domlan et al.[2011] proposes a multi-model approach for separation of sand oil. For model mismatching problem, model re-training [Mcbride et al., 2011; Yin et al., 2014], or model structure and parameters re-adjusting [Wallace et al. 2005; Giantomassi et al., 2011; Thomas and Suhner, 2015] methods are usually used.

Froth flotation of bauxite is a complex nonlinear system with multiple parameters and large time delay. Influence of the recycled water, variation of the ore and other factors make the pH value be unstable. Especially, because the ore resources is becoming exhausted, the ores come from many different deposits. Most of them are of very low grade (A/S, ratio of the mass content of Al_2O_3 and the SiO_2). Although blending is used to try to make the feed homogeneous, properties of the feed change frequently, and therefore the pH

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value have to change. So, model mismatch occurs after the single model or multi-models with simple combination runs for a period of time. They are found to be not adapt to the online estimation of pH value.

In this study, multiple neural network models with self adaption is investigated. Firstly, the online estimation problem and the process characteristics are analyzed and described. Then, the models are developed. Simulation results using industrial data are shown and compared. Finally, conclusions are drawn.

2. ANALYSIS AND DESCRIPTION OF THE ONLINE ESTIMATION OF PH

In the froth flotation, ores with different properties need different pH value to achieve the best flotation performance. So, when the ore changes, the floatability of the ore and a new suitable range for the pH value will be prescribed by lab tests. When the feed is stable, the pH value is influenced by the operating conditions, including the flow rate of the ore, the flow rates of the new water and the recycled water, and other uncertain factors. That is, the pH fluctuates around a prescribed range due to the control of the operators when the feed is stable. When a new type of ore comes, the prescribed range of the pH changes.

It is found by experience that the bauxite ore reacts with the pH regulator (Na_2CO_3) which is added into the process with the mill feed, so that some of the pH regulator is consumed by the ore in the milling-classification section. But the reaction mechanism has never been studied. When the ore feed is stable, the dosage of the regents (the frother and the collector, etc.) is rarely adjusted, and only the dosage of pH regulator is adjusted once an hour. So, the froth image features are closely related to the pH. Meanwhile, In view of the close relationship between the froth image features and the flotation performance [Shean and Cilliers, 2011; Holtham and Nguyen, 2002], froth features are selected as the inputs for pH estimation. Relationships between the froth features and the pH value are analyzed as the following.

2.1 The froth features and the pH with stable ore feed

With the machine vision installed above the first cell of the rough flotation, 165 pictures were obtained except the fuzzy ones with a relatively stable feed. 13 features, including the mean value of the bubble size, mineral load rate, froth colour (Mean value of R, G, B), froth velocity, froth stability, texture, kurtosis of the bubble size, foam hue, froth red component, skewness of the bubble size and gray value of the froth image, were extracted using the algorithms of watershed segmentation, blocking matching, co-occurrence matrix, etc. [Yang et al., 2008; Gui et al., 2013; Tang et al., 2009; Morar et al., 2006]. Measuring methods of the froth velocity, froth stability, bubble size, kurtosis of the bubble size and texture are shown in Table 1.

The pictures can be classified into 3 types according to the pH value, as the representative ones for each type shown in Fig.1. It can be seen that, the froth features (obviously the bubble size) vary with the pH value. In Fig.1 (a), the pH value is low, bubble size is small and dense with high load of minerals, and the colour is blacker; in Fig.1(b), at the higher pH value, the bubble size becomes larger with high load of minerals; in Fig.1(c), the bubble size is the largest, while the load is small, and the bubbles are easy to collapse. In all of the pictures, 18%, 73% and 9% are of the type in Fig.1(a), Fig.1(b) and (c), respectively.

Table 1 Main features of froth measuring methods

Froth features	Measuring methods
Froth velocity	Block tracking method is used to estimate the movement of the bubbles. Froth sub-block SIFT (Scale Invariant Feature Transform) features are extracted based on Kalman filtering, and then froth velocity can be obtained by sub-block SIFT features registration [Liu et al., 2012].
Froth stability	Define, $\delta(i,j)=\begin{cases}1, & \lvert f_1(i,j)-f_2(i,j)\rvert > k\\ 0, & \lvert f_1(i,j)-f_2(i,j)\rvert \le k\end{cases}$, then $S=1-\sum_{i=1}^{M}\sum_{j=1}^{N}\delta(i,j)\Big/(M\cdot N)$, Where $f_1(i,j)$ and $f_2(i,j)$ are the gray value of the (i,j)th pixel in two successive images, respectively; k is stabilization threshold (set to 50 by tests in this study), M and N are row and column number of pixels in the image. S shows a trend of stability, the larger the S value, the more stable the froth.
Bubble size	Watershed algorithm is used [Bieniek et al., 2000] for froth image segmentation to obtain bubble size (bubble area) in pixels, which could be converted to actual value in meters by $D=D_p\cdot\delta$, where D_p is bubble size in pixels, δ is pixel area ratio constant, whose value is 0.0256 mm^2, D is actual value in meters.
Kurtosis of bubble size	Kurtosis shows the probability distribution of bubble size. It can be expressed as, $C=n\sum_{i=1}^{n}(D_i-\overline{D})^4\Big/\left[\sum_{i=1}^{n}(D_i-\overline{D})^2\right]^2-3$, where $\overline{D}$ is the average bubble size, D_i is the ith bubble's size, n is the number of bubbles in the image.
Texture	Froth texture are extracted using the Grey-Level Co-occurrence Matrix [Haralick et al., 1973] method. GLCM element values distribution relative to the main diagonal is closely related to froth texture, the greater the value is close to the main diagonal, the coarser the texture is.

Gray correlation analysis is carried out to find the correlation degree between the froth features and the pH value. Finally, velocity, mean value of bubble size, foam hue, stability, and mean value of the R value are found to be most related to the pH value. The ranges of these features corresponding to the three types of pictures are shown in Table 2. The range is obtained by using [u-s, u+s], where u is the average value of the feature and s is the standard deviation.

Some of the features has a variation trend with the pH value, but the others do not. Thus, the relationship is complex with