Information Sciences 360 (2016) 244–255

Contents lists available at ScienceDirect

Information Sciences

journal homepage: www.elsevier.com/locate/ins

Multiple-model predictive control for component content of CePr/Nd countercurrent extraction process[☆]

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ARTICLE INFO

Article history:
Received 16 January 2016
Revised 25 April 2016
Accepted 26 April 2016
Available online 30 April 2016

Keywords:
Component content control
Multiple models
Multivariable
Predictive control
Rare earth countercurrent extraction

ABSTRACT

A new multiple-model predictive control scheme is proposed for the control of the component content in the rare earth extraction process. Multiple local linear models with two-input and two-output of the rare earth countercurrent extraction process are constructed, each of which is established under an operation condition. A component content predictive controller is designed for a local linear model, based on the dynamic compensation of the extraction liquid flow and the scrubbing liquid flow. A switching algorithm based on the minimum accumulative error is formed to select the most appropriate model and controller to meet the productive purity requirements. Simulation results for the CePr/Nd countercurrent extraction process are presented to show the desired performance of the proposed approach.

1. Introduction

Rare earth (RE) metals have been widely used as important materials in various fields, such as metallurgical industry, petrochemical and the national defense military industry. However, rare earth extraction process is usually characterized by nonlinear behavior, large time delays and strong coupling of various process variables, and it is the typical complex industrial process. Thus, it is of great significance in practice to realize the optimal control of the rare earth extraction process (REEP) to ensure product quality, reduce energy consumption and improve the economic efficiency of enterprises.

At present, many different kinds of models are widely used for the rare earth extraction and separation process. An extraction equilibrium calculation model was proposed in [23] to solve the optimization problem of multi-component content in extraction system. However, the model has characteristics of the ideal experiment and it is hard to reflect the dynamic characteristics of the extraction process. A modeling method of neural network was proposed in [8]. but the model accuracy largely depends on the sample data and the training results of neural network. A simplified bilinear dynamic model was presented in [11], which has high prediction accuracy in local region and exists large predictive error while the operating range greatly changed. A method for soft-sensor based on multiple models was developed in [10]. The established model is simplified by reducing its order, and using five extraction stages to measure the element component content online, but

☆ This work was supported in parts by the National Key Basic Research Program of China under grant 2014CB360502, by the National Natural Science Foundation of China under grant 51174091, 61364013 and 61563015, by the Special Innovation Fund for Postgraduate of Jiangxi Province under grant YC2015-S241.

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http://dx.doi.org/10.1016/j.ins.2016.04.031
0020-0255/

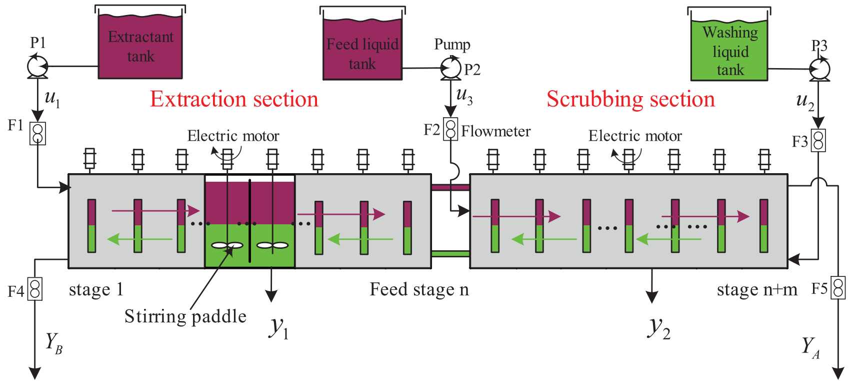

Fig. 1. Structure of rare earth countercurrent extraction process.

there also exists some problems like the huge number of models and large calculation. Besides, several mathematical models of the REEP were presented in [14,21,26]. Unfortunately, most of them are static models or they are too complicated, so it is hard to be used as predictive models. On the other hand, there are few control methods for the REEP. Aiming at the problems in establishing accurate mathematical model and realizing the automatic control of the REEP, an optimal control method of rare-earth countercurrent extraction separation process is proposed in [25]. It integrates the case-based reasoning technique with the component content soft sensing technology based on neural networks. However, it is difficult to guarantee its reliability when new conditions emerge.

Generalized predictive control (GPC) is one of the widely used model predictive control (MPC) methods [4], which has been successfully applied to industrial processes [19,20,22,27]. It has capacity of dealing with the nonlinearity and uncertainty of dynamic systems and handling various constraints associated with the control process. Thus the GPC is suitable for some complicated uncertain systems, such as the REEP. An application of GPC for the REEP was designed in [18], and it realizes the automatic control of constituent content during rare earth exaction process.

In this paper, a multiple-model generalized predictive control (MMGPC) method is developed for a double-input double-output system motivated from the productive processes of CePr/Nd extraction in an enterprise. The subtractive clustering algorithm is employed to determine the number of steady-state operation point based on the dynamic data of CePr/Nd extraction process. A local linear model is established at each steady-state operation point, then a switching strategy is designed to select the matching model and its corresponding controller. The GPC is applied to realize the component content control of the REEP. Different from our early work in [18], which studies control of rare earth process by simplifying it as a multiple-input single-output system, this paper develops a new solution framework of multiple-model predictive control for the multiple-input multiple-output system simplifying the rare earth countercurrent extraction process to close to the practical situation on site. The contributions of this paper are (i) development of a new multiple-model predictive control framework for the rare earth countercurrent extraction process with two input two output for improving the system performance. (ii) Summarization of the methods about how to adjust the input variables when the disturbance occurs in the running process, which gives a guidance to the industry site. (iii) Simulation of the predictive control scheme to control of the rare earth countercurrent extraction process with actual data from a rare earth company to show its desired performance.

The rest of this paper is organized as follows: Section 2 describes the rare earth countercurrent extraction process. The multiple models of the rare earth countercurrent extraction process are established in Section 3 and the controller is designed in Section 4. Section 5 presents simulation results to show the desired system performance. Conclusions and possible extensions are discussed in Section 6.

2. Description of rare earth countercurrent extraction process

Due to the low separation coefficients among rare earth elements, a large amount of mixer-settlers are generally connected in cascade and make the extracted material multiple-contact in the aqueous phase and organic phase in rare earth industry. In this way, we can achieve an effective separation of rare earth elements, and obtain two or more high purity and high yield RE production [23]. The REEP is depicted in Fig. 1, which involves the extraction section composed by n stages mixer-settler, the scrubbing section composed by m stages mixer-settler, the hard extracted product Y_B in aqueous phase from the 1st stage, and the easy extracted product Y_A in organic phase from the $(n+m)$th stage. The organic phase flows in the opposite direction of the aqueous phase.

As shown in Fig. 1, the extraction liquid is injected into the 1st stage in the extraction segment with a flow rate u_1, which flows from left to right and together with the feed liquid. The feed liquid is poured into the nth stage feed tank with a flow rate u_3. The scrubbing liquid is added at the $(n+m)$th stage with a flow rate u_2, whose counter-current flow is from right to left. During the REEP, a sensitive detecting point is respectively set in the extraction and scrubbing section, which