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ScienceDirect
ISA Transactions 46 (2007) 49–57
www.elsevier.com/locate/isatrans

Synthesis of nonlinear adaptive controller for a batch distillation

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Received 6 November 2005; accepted 22 May 2006
Available online 22 January 2007

Abstract

A nonlinear adaptive control strategy is proposed for a binary batch distillation column. The hybrid control algorithm comprises a generic model controller (GMC) and a nonlinear adaptive state estimator (ASE). The adaptive observation scheme mainly estimates the imprecisely known parameters based on the available tray temperature measurements. The sensitivity of the proposed estimator is investigated with respect to the effect of initialization error, unmeasured disturbance and uncertainty. Then, a comparative study is carried out between the derived nonlinear GMC–ASE controller and a traditional proportional integral law in terms of set point tracking and disturbance rejection performance. The study also includes the effect of measurement noise and parametric uncertainty on the closed-loop performance. The proposed adaptive control algorithm is shown to be quite promising due to the exponential error convergence capability of the ASE estimator in addition to the high-quality control action provided by the GMC controller.

Keywords: Generic model controller; Adaptive state estimator; Adaptive control algorithm; Batch distillation

1. Introduction

Batch distillation is a well-known separation process that is mostly used in many chemical, biochemical, and food industries for the production of small amounts of products with high added value. A single batch distillation column can produce several products from a multicomponent feed mixture within a single operation, whereas a train of columns is required to separate the same mixture continuously.

The flexibility provided by a batch rectifier gives rise to challenging control problems that are basically owing to the nonstationary, nonlinear and finite time duration nature of the underlying dynamics. The batch distillation is inherently an unsteady state process, and in such a situation, there is no normal condition at which the controllers can be tuned. Hence, it is really a challenging task to obtain a satisfactory closed-loop response [1,2].

It is recognized that the conventional proportional integral (PI) and proportional integral derivative (PID) controllers provide poor performance due to the nonstationary nature of batch rectifiers [3]. Frattini-Fileti and Rocha-Pereira [4] applied the gain scheduled PI control strategy on a binary batch distillation. The authors proposed the predictive and adaptive control schemes to confront the time-varying nature of the batch rectifier. Li and Wozny [5] showed that the optimal profiles cannot be tracked with conventional linear controllers. Subsequently, Li and Wozny [6] again showed that a predefined optimal policy can be tracked via an adaptive control law to realize the optimum of multiple-fraction batch distillation. In their procedure, a recursive least square estimation with a variable forgetting factor is used for the online identification and to follow the rapidly changing process dynamics.

Barolo and Berto [7] proposed a control strategy that is derived in the framework of nonlinear internal model control [8]. To estimate the distillate composition from the selected tray temperature measurements, the authors used the extended Luenberger observer [1]. The derived control law was then successfully applied on a binary and a ternary batch rectifier. Dechechi et al. [9] have shown that the nonlinear model predictive controller provides good results for overhead composition regulation. In their approach, an extended Luenberger observer is employed for state estimation. Alvarez-Ramirez et al. [10] developed a strategy that comprises a controller (classical PID with antireset windup) and an observer to estimate the modeling error. A drawback of

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doi:10.1016/j.isatra.2006.05.001

Nomenclature

dt	Derivative time
D	Distillate rate
D_s	Bias of PI controller whose output is D
e, e_D	Error to the controller
K_C, K_{CD}	Gain of PI controller
K_1, K_2	Tuning parameters of the generic model controller
L_n	Internal liquid flow rate leaving nth tray
m	Number of manipulated variables
m_B	Holdup in the still pot
$\dot{m}_B$	Time derivative of m_B
m_D	Holdup in the reflux drum
$m_{D\text{sp}}$	Set point value of m_D
m_n	Liquid holdup on the nth tray
n	Number of states/tray index
q	Number of measurable disturbances
R	Reflux flow rate
R_s	Bias of PI controller whose output is R
t	Time at which the PI controller produces the outputs
T_D	Temperature in the reflux drum
u	Vector of manipulated inputs
V_B	Vapor boil-up rate
V_n	Internal vapor flow rate leaving nth tray
x	Vector of state variables
$\hat{x}$	Vector of estimated states
x_B	Liquid composition in still pot
$\dot{x}_B$	Time derivative of x_B
x_D	Distillate composition
$\dot{x}_D$	Time derivative of x_D
$x_{D\text{sp}}$	Set point of x_D
y	Output variables
y_B	Composition of boil-up vapor
y_c	Vector of calculated compositions (sensor outputs)
y_m	Vector of measured states
y_{sp}	Set point of y

Greek letters

ε	An unknown and bounded function in the adaptive estimator
τ_i, τ_D	Integral time for PI controllers
θ	Vector of augmented states

their strategy [3] is that they strongly rely on an accurate model of the batch distillation process. Subsequently, Oisiovici and Cruz [11] proposed an inferential control structure in conjunction with an extended Kalman filter [12]. They applied this control scheme on a high-purity multicomponent batch distillation column. Han and Park [13] have used the quasi-dynamic estimator [1] to estimate the distillate composition in a closed-loop batch rectifier. In their research work, a nonlinear wave theory [14] has been used to develop the nonlinear model-based controller. Then, Monroy-Loperena and Alvarez-Ramirez [3] presented a method for the identification and control of a batch distillation process. In their work, the feedback controller is designed in the framework of robust nonlinear control [15] with modeling error compensation techniques.

The success of a nonlinear model-based control system greatly depends on the performance as well as robustness of the state estimator. So far, many observation schemes have been designed and applied with good results on the batch distillation processes [1,16–20].

This research interest is towards developing an adaptive control algorithm for a batch distillation column. The control strategy is designed in the framework of generic model control [21] (GMC), combined with an adaptive state estimator [22,23] (ASE). The GMC is a method of choice because it is an efficient strategy [24] to implement the nonlinear process model-based control, and it has been shown to be very successful in laboratory-scale [25] and industrial-based applications [26,27]. Here, the adaptive observation scheme is mainly employed to estimate the badly known parameters from the readily available temperature measurements instead of using the directly measurable product compositions because the composition analyzers provide large delays in the response in addition to high investment and maintenance costs.

In brief, two major contributions of the present work are highlighted in the following:

(i) It is true that most of the nonlinear observation schemes involve significant design complexity. Actually, the large predictor model and the complex structure of the closed-loop observation technique complicate the overall design. To reduce the design complexity, in this study, an adaptive state estimator has been developed for a rigorous batch distillation column. This estimator has simple structure and the predictor model includes only two component continuity equations of the example process. We must note that the proposed ASE approach only estimates the states as per the GMC controller requirements. Like other observation algorithms, it does not compute all the process states. The estimation scheme that is proposed here for a batch distillation is not reported in the scientific literature.

(ii) In addition, an adaptive GMC–ASE control law has been synthesized for the batch distillation. The proposed control structure provides high-quality performance mainly due to the exponential error convergence capability of the ASE estimator. To the best of our knowledge, the design technique of the GMC–ASE control strategy for the batch distillation column is a new one.

In this study, first the open-loop performance of the proposed adaptive estimator has been inspected under initialization error in the imprecisely known parameters, unmeasured disturbance, and uncertainty. Subsequently, the adaptive controller is implemented on the simulated batch rectifier. The closed-loop performance of this control technique has been compared with that of the conventional PI controller. The closed-loop