Abstract

Batch distillation is a complex and higher order system, in which the batch operation mode is a difficult task for estimation and control. During the entire operation, the operating conditions varies over a wide range of values with respect to time, and thus, the estimator should be designed to deal with the time-varying nature of the batch column. The online estimation of a continuous process is not a difficult process, but for batch distillation, it is a difficult task as the process may introduce time-delay. Hence, a discrete Kalman filter for binary component distillation has been developed and simulated, which estimates the temperature of the different trays of the column to obtain product purity. Operating the temperature at the required levels will lead to purity of the end components. In this paper, authors concentrated on trays T3 and T6, as these trays play a vital role in estimating the purity of the top and bottom products.

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1 Introduction

In control systems, state estimation is used to calculate approximately the internal state of any given real system by using its input and output information. In control theory problems, understanding the internal state of the system is necessary as to stabilize the system with state feedback. In such a case, the Kalman filter is accurate for stochastic systems. It is a two-step recursive algorithm for compensation of different noises.

In a batch distillation process, the control of the composition profile plays an important role, but it is very difficult to build on-line analyzers for the batch processes as they give delayed responses. Therefore, a stochastic estimator was developed by R. M. Oisiovici et al. (2000) [1] for an accurate composition profile by varying the reflux ratio. The basic estimation idea was understood from the “State Observers and State Feedback” in Process Control. Introduction to Communication, Control, and Signal Processing by Alan V. Oppenheim et al. [2]. The Kalman filter algorithm basic probability theory was studied from the “An Introduction to Kalman filtering” by Greg Welch and Gray Bishop [3]. The Kalman filter as a state observer and its limitations were taken from the “The Kalman Filter as State Observer. Optimal Filtering” by Anderson Moore [4]. An ELO (Extended Luenberger Observer) designed by David G. Luenberger (1971) [5] was used in the estimation of the reagent-compositions in a combined reactor, but the ELO is not an efficient deterministic estimator and could not yield efficient results in presence of the plant/process mismatch and/or in the presence of noises. Hence, it was concluded that the Kalman filter is better and robust compared to the ELO (when high degree of noises are expected). The accomplishment of the Kalman filter in state estimation in the presence of model-plant mismatch was studied from the “Evaluation of Adaptive Extended Kalman Filter for State Estimation in the presence of Model-Plant Mismatch” by Vinay A. Bavdekar et al. [6]. The difference between the Kalman estimation and the reduced order model was taken from the “Monitoring of a Distillation Column using Modified Extended Kalman Filter and a Reduced Order Model” by Dae Ryook Yang et al. [7]. S. Abraham Lincon and D. Sivakumar [8] designed a three tank system an
both state and parameter fault estimation, which uses the model-based approach.

The main aim of this project is to design a Kalman filter for the batch distillation column so as to obtain a pure composition at the end of the process for estimating the temperature of the different tray sections by varying the current reflux ratio and heater profiles.

2 The Kalman Filter

The stochastic state space model of the system is given by

\[\dot{X}(t) = \Phi * X(t) + \Gamma * U(t) + W(t)\]
\[Y(t) = c * X(t) + V(t)\]  

(1)

Linearizing and discretizing (at the required sampling frequency) the above model, we get...

\[X(k + 1) = A * X(k) + B * U(k) + W(k)\]
\[Y(k) = c * X(k) + V(t)\]  

(2)

Where ‘W’ is the process noise which describes all the disturbances that acts on the system.

‘V’ is the measurement noise which is related to the sensors.

‘W’ is assumed that the process noise is a Gauss-distributed, random variable with mean as zero, and having the covariance as Q and is independent of the process noises or the states of the system which have occurred at any previous time.

\[P(W_i) \sim N(0, Q)\]
\[E[W_i W^T_j] = \begin{cases} Q, & i = k \\ 0, & i \neq k \end{cases}\]  

(3)

The measurement noise is a Gauss-distributed, random variable with mean as zero, and having the covariance as R.

\[P(V_i) \sim N(0, R)\]
\[E[V_i V^T_j] = \begin{cases} R, & i = k \\ 0, & i \neq k \end{cases}\]  

(4)

The set of measurements are collected from time 0 to k.

\[Y^k = \{Y(0), U(0), Y(1), U(1), \ldots, Y(k), U(k)\}\]
\[\bar{X}(k) = \hat{X}(k \mid k) = E[X(k) \mid Y^k]\]  

(5)

\[\hat{X}(k \mid k)\] is the estimate of the state at time instant k, where, the measurements are given up to k. Under weak conditions, the optimal estimate \[\hat{X}(k \mid k)\] is the conditional mean of \[\bar{X}(k)\].

The Kalman filter was developed in two steps: prediction step and correction step. The prediction step is said to be the time update step and the correction step is said to be the measurement update step.
estimation of the unknown variables of the system.

A. Prediction Step:
In the prediction step, the estimates of the error covariance and the current state are calculated for forwarding time. These estimates are known as the Priori estimates.
The Kalman filter algorithm starts with the optimal initialization of the $\hat{X}_0$ (initial state estimate) and $P_0$ (initial error covariance).

\[
\hat{X}(k|k-1) = A \hat{X}(k-1|k-1) + B U(k-1)
\]
\[
P(k|k-1) = A P(k-1|k-1) A^T + Q
\]
\[
\hat{Y}(k|k-1) = C \hat{X}(k|k-1)
\]

B. Correction Step:
\[
L(k) = P(k|k-1) C^T [C^T P(k|k-1) C + R]^{-1}
\]
\[
e(k) = Y(k) - \hat{Y}(k|k-1)
\]
\[
\hat{X}(k|k) = \hat{X}(k|k-1) + L(k) e(k)
\]
\[
P(k|k) = [I - L(k) C] P(k|k-1)
\]

Where,
\[
\hat{X}(k|k-1)
\] is the predicted mean, the state prediction which is conditional mean,
\[
P(k|k-1)
\] is the predicted covariance, which deals with the uncertainties associated with the state noise,
\[
e(k)
\] is the innovation, that is the deviation or error between the actual and estimated states,
\[
Y(k)
\] is the output available with the information of $W(k)$ and $V(k)$,
\[
L(k)
\] is the optimal Kalman gain matrix,
\[
\hat{X}(k|k)
\] is the corrected mean, and
\[
P(k|k)
\] is the corrected covariance.

3 Batch Distillation Column

Distillation is the process of separating the components from a given liquid mixture by optimal condensation and evaporation. Here, in this project, we use a mixture of Iso-Propyl Alcohol (IPA) and water. Once the feed is ready, it is heated to the required temperature, collecting the IPA at the bottom and the water gets evaporated and will be the condensate. To control the temperature, we feed the condensate (called reflux) back to the column and also control the heater current of the boiler. Thus, the end result should be IPA rich stream as the bottom product and water rich stream as the top product. The temperature of the composition at each tray is measured with thermocouples. The estimation and control of these two temperature may lead to highest purity of the end product. The two stages where the temperature is estimated and controlled in this project are tray 3 and tray 6 (T3 and T6). The stages are much concentrated as those are the highest oscillating temperature where just the
temperature.

The industrial distillation column control typically relies on one (or maybe two) carefully located tray temperature sensors. The distillation setup used in the project is shown in Fig. 1.

Here, at each sample period, the Kalman filter (state estimator) is used to estimate the temperature profile along the column, current feed composition, and to set the control moves that will drive the column optimally towards the MEP (minimum error profile) target steady state; this being the closest match possible to the desired operating condition with the current feed composition.

4 Results

An estimator for the binary distillation column is further designed and simulated. In order to test the algorithm, we first designed the estimator as per the Wood and Berry model (only for simulating the algorithm) keeping only the reflux ratio and heater current as constants. Firstly, keeping the reflux ratio and the heater currents constant, we gave a certain temperature for both T3 (68) and T6 (72) in the algorithm to track. The graph for the MIMO system is shown in Fig. 2.
Fig. 2. Temperature control of T3 and T6 when reflux and heater current are kept constant.

Fig. 3. Temperature estimation and control of T3 and T6 with Varying reflux and heater current.

The Wood and Berry Model is as follows:

\[
G(s) = \begin{bmatrix}
12.8 e^{-s} & -18.9 e^{-3s} \\
16.7s + 1 & 21s + 1 \\
6.6 e^{-7s} & -19.4 e^{-3s} \\
10.9s + 1 & 14.4s + 1
\end{bmatrix}
\]

Secondly, it was checked the algorithm for the identified model taken from [9-10] with a certain temperature for T3 and T6 by varying both the reflux ratio and the heater current, and the result of the estimator is shown in Fig. 3. and Fig. 4. The estimation of temperatures at the trays T3 and T6 are given in Fig. 3. Where as the estimation of temperatures for the trays T4 and T5 are given in Fig. 4.

In addition, the Vinaya-Priya identified model is as follows:
The Kalman filter has been designed for a binary distillation column so that we can estimate the temperature profile along the column, once if the estimates of the temperature are available along the column they can be controlled over the process. The temperature (desired) can be maintained by changing the reflux ratio as well as the heater current.

\[
G(s) = \begin{bmatrix}
-0.16 e^{-0.01s} & 0.6 e^{-1.19s} \\
0.01s + 1 & 0.05s + 1 \\
-0.04 e^{-0.01s} & 0.49 e^{-0.47s} \\
0.02s + 1 & 0.19s + 1
\end{bmatrix}
\]

Fig. 4. Temperature estimation and Control of T4 and T5 with Varying reflux and heater current

References


