Distillation Process Fault Detection by CUSUM Test

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Keywords

Black-box modeling, NARMAX model, CUSUM test, Fault detection, industrial processes.

Abstract

In this work, The CUSUM (Cumulative Sum) test is employed to determine the real operating conditions of nonlinear processes as a separation unit. To do this, the normal behavior of the system is first predicted by means of a Nonlinear Auto-Regressive Moving Average with eXogenous input (NARMAX) model and then the residual between the real and estimated output of system is evaluated at each time by taking new observations of the process output under consideration. Finally, the thresholds on the CUSUM test are derived such that when the updated residual exceeds the thresholds an alarm is triggered.

1. Introduction

Monitoring of real processes, such as those in chemical and petrochemical industries, is necessarily required for satisfying the highest level of product quality. Detection of abnormal situations allows to the consequences of a dangerous behavior. Chemical processes are complex large-scale plants which need detecting any abnormal mode before its propagation in all components. Several research works have been appeared during the last few decades: analytical redundancy and parity space techniques, or the parameter identification methods [1], [2].

In the literature of the anomaly detection and diagnosis strategies, various methods were developed, and they are divided into two standard classes: data-based and model-based methods [3], [4]. Model-based anomaly detection techniques consist of two steps: the first one is the residual generation and the second one is the residual evaluation. For the residual generation purpose observer-based approach [5] and black-box modeling method are also most often applied [2]. Here we used the black-box modeling by employing a NARMAX structure because it shows a good performance of prediction [6], [7]. In fact, after generating a residual signal for a system studied, the remaining work in the second step is the residual evaluation and decision making, which can be realized by the statistical hypothesis testing and statistical distances [6], [9].

In this research, a NARMAX model is first determined to describe the process dynamics. Then the CUSUM test was utilized to the residual obtained from the NARMAX representation to detect abnormalities in the distillation unit. The remainder of the paper is structured as follows: in Section 2, the process studied is presented. Section 3 contains the results of the black-box modeling.

This section also presents the proposed FD method. The results of the FD technique are further evaluated in Section 4. Section 5 concludes the paper.

2. Case study

The system studied in this research is a separation unit established in the laboratory scale. The column was used to separate the binary, toluene methylcyclohexane mixture. Figure 1 represents the general view of the separation unit. The feed tank comprises a mixture to be divided with a mass composition at 23% in methylcyclohexane.

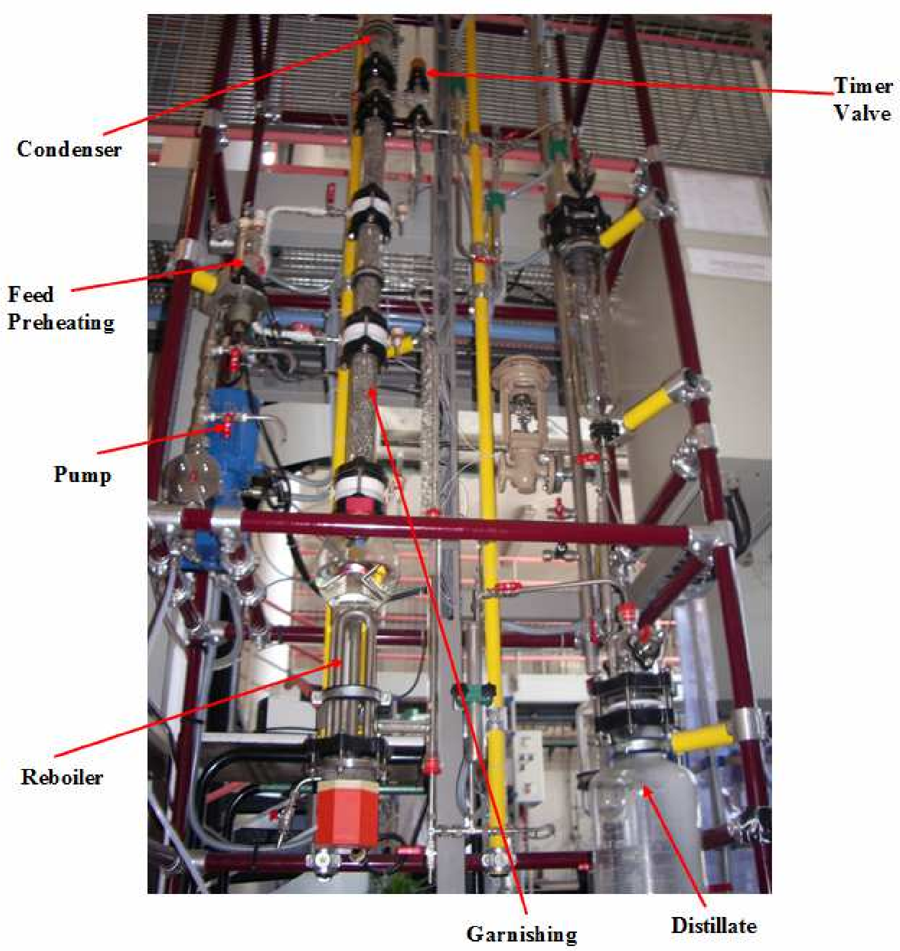

Fig. 1: Distillation column: general view of the process

The process is equipped with twelve temperature sensors which measure continuously the temperature at various points of the column. The system takes as output the overhead temperature (T_d) and as inputs the pressure drop (ΔP), the reflux timer (R_t), the heating power (Q_b), the preheating power (Q_f) and the preheating temperature (T_f) [7].

3. Proposed Fault Detection Technique

In this work, a FD scheme based on the combination of the NARMAX model and the CUSUM test is developed. The NARMAX model is the extension of an ARMAX model. For describing the dynamics of MISO nonlinear systems this structure is represented by [6], [7]:

$$y(t) = f\left(y(t-1), \ldots, y(t-n_y), u_1(t-d_1), \ldots, u_1(t-d_1-n_{u1}), u_p(t-d_p), \ldots, u_p(t-d_p-n_{up}) + e(t-1), \ldots, e(t-n_e)\right) + e(t) \quad (1)$$

where $y(t)$ is the output, $u_i(t)$ is the i^{th} input, and $e(t)$ is the error; p represents the number of the process inputs. The variables n_y, n_{ui},..., n_{up}, n_e indicate the regression orders of the output, inputs, and error, respectively. d_i represents the input delay. f denote unknown nonlinear function. This function takes a polynomial expansion in this work [6].

3.1 CUSUM Test

The CUSUM test introduced in [8], [9] is an efficient tool for verifying the normal behavior. This test uses the residual signal ε generated from a NARMAX model for detecting a modification in the residual mean at undetermined time points. As the sense of variation in the residual mean is unknown the CUSUM test employs two rules. The tests for detecting positive and negative shifts (diminution or augmentation in the residual mean) are:

For a negative shift in the residual mean

$$\begin{cases} T_N = \sum_{t=1}^{N}\left(\varepsilon(t) - \theta_0 + \dfrac{\delta}{2}\right) \\ M_N = \max\limits_{0\le t\le N}\left(T_t\right), \quad T_0 = 0 \\ \text{Alarm when } \; M_N - T_N > \lambda \end{cases} \quad (2)$$

and for a positive shift in the residual mean:

$$\begin{cases} U_N = \sum_{t=1}^{N}\left(\varepsilon(t) - \theta_0 + \dfrac{\delta}{2}\right) \\ m_N = \min\limits_{0\le t\le N}\left(U_t\right), \quad U_0 = 0 \\ \text{Alarm when } \; U_N - m_N > \lambda \end{cases} \quad (2.A)$$

where $\varepsilon(t) = y(t) - \hat{y}(t)$ is the residual at time t, U_N et T_N represent the cumulative sums at time t, λ is the threshold of test, θ_0 indicates the mean of residual signal in normal mode, and δ is a priori chosen minimum jump magnitude in the residual mean.

It is assumed that the sequence of the residual ε follows a normal distribution. The threshold value λ used for detecting any shift from the normal mode of the supervised process can be defined by the relation ($\lambda = 2 * h * \sigma / \delta$) where $h = 2$ for Gaussian densities and σ indicates the standard deviation of the residual [10].

4. Experimental Results

4.1 Black-box Modeling Results

For determining NARMAX model, 3487 samples of data from the distillation process were recorded with the sampling period of 11 (s) (Figures 2 and 3). The latter presents the evolution of the input variables in the interval [1540 (s) 2365 (s)] for better readability. The data set and the complete black-box modeling procedure of the distillation system are described in [6]. The obtained NARMAX model is shown in Table 1.

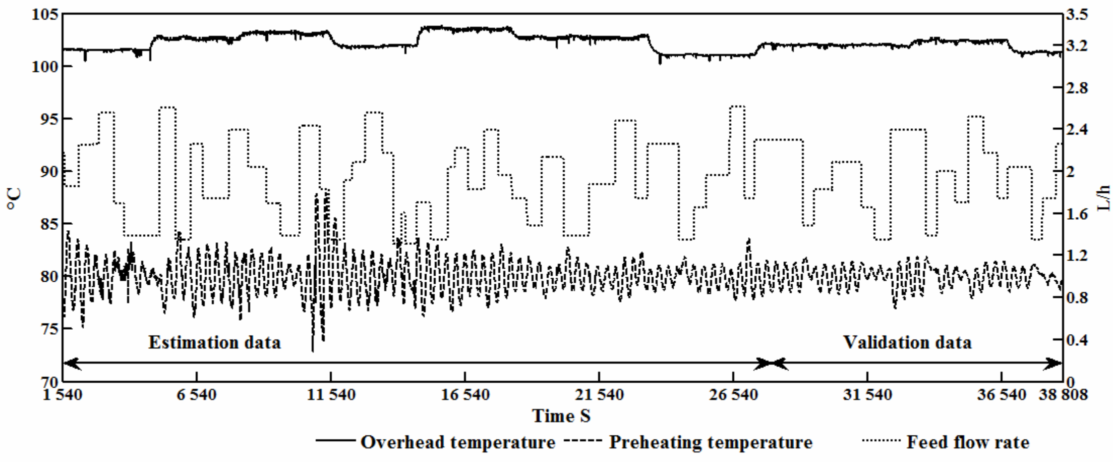

Fig. 2: Measurements of the overhead temperature, preheating temperature and feed flow rate

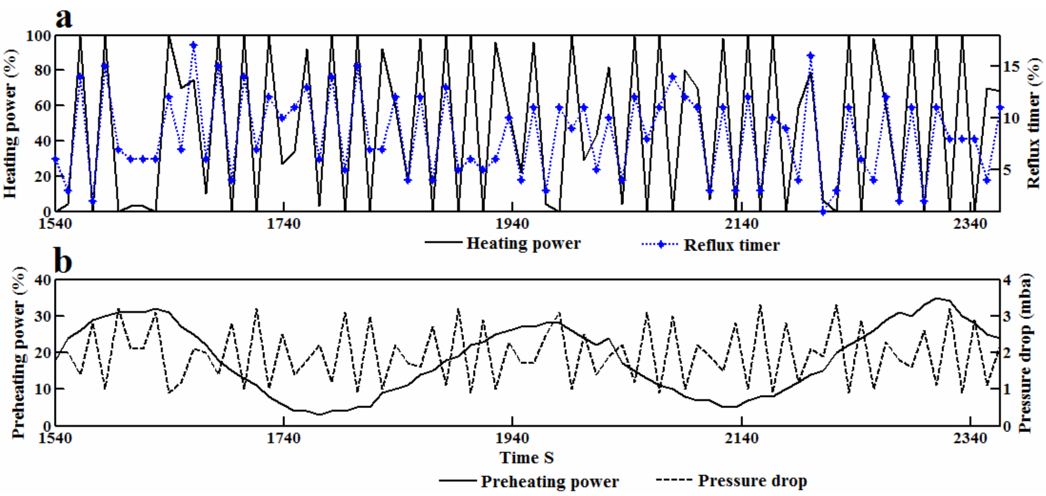

Fig. 3: Measurements of the preheating power, pressure drop, heating power and reflux timer

The obtained NARMAX model is given by:

$$\begin{aligned} T_d(t) = &-0.2601T_d(t-1) - 0.6901T_d(t-2) + 0.0228Q_b(t-1) - 0.0427Q_f(t-4) - 0.0558Q_f(t-5) \\ &+ 0.0685\,R_t(t-1) + 0.1053R_t(t-2) + 0.0165\Delta P(t-1) - 0.0199\Delta P(t-2) - 0.0971T_f(t-5) \\ &- 0.0027T_f(t-6) + 0.3524e(t-1) + 0.4175e(t-2) + 0.2139T_d(t-2)R_t(t-1)\Delta P(t-5) \\ &+ 0.1093R_t(t-6)\Delta P(t-1)\Delta P(t-6) - 0.1050Q_b(t-1)R_t(t-4)\Delta P(t-1) \end{aligned} \tag{4}$$

4.2. Fault detection results

In this subsection, NARMAX model is integrated with CUSUM test to detect abnormalities in a separation unit. Towards this end, the supposition that the residual variance rests unaffected and the change only occurs in residual mean is retained. Consequently, the mean θ_0 and the standard deviation σ will be estimated by means of fault-free data obtained during normal mode.

In order to verify the efficiency of the developed FD technique, the detection of a sudden augmentation of the heating power (Q_b) to 100% was chosen. This abnormality is presented at instant 10835 (s) and causes a small augmentation in the output of the system (T_d) (Figure 4). This fault must be detected by the CUSUM test at their inception. The time evolution of the CUSUM test before and after the fault has been obtained according to Eqs. (2) and (3). Figure 5 shows the evolution of CUSUM test for the studied fault. This evolution indicates that the adopted method successfully detected the abnormality by exceeding the threshold value.

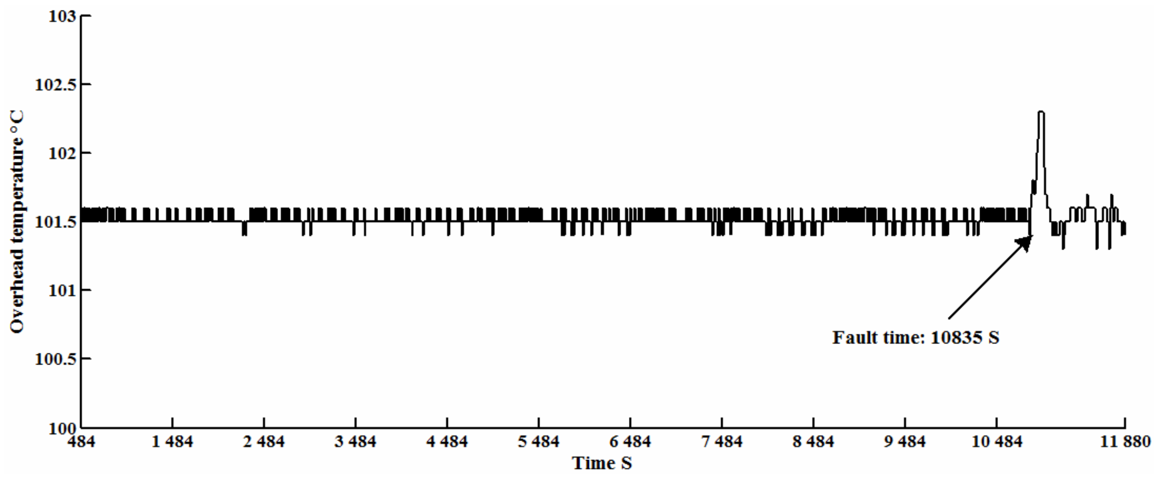

Fig. 4: Time evolution of the output of process produced by the selected fault

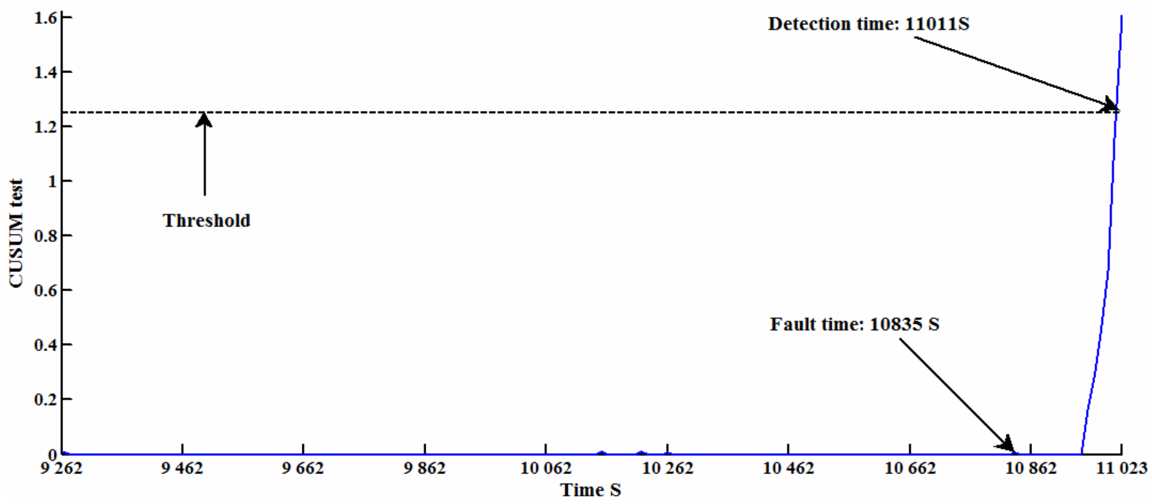

Fig. 5: Results of CUSUM test for the selected anomaly

The CUSUM test consists in choosing a minimum allowed amplitude value in the residual mean δ to be detected, and performing two rules at the same time (Eqs. (2) and (3)), because the sense of the variation is not defined a priori (augmentation or diminution of mean). The final decision about the fault is taken corresponds to the rule which arrests first, and the approximate of the fault time is the last maximum or, respectively, minimum time before detection.

As it is indicated Figure 5, the alarm condition is triggered when the CUSUM test surpasses the threshold λ. It is essential to note that the abnormality arises at 10835 (s) was detected at 11011 (s), i.e., with the delay of 165(s). This delay is principally due to the evolution of the separation system, the change magnitude, and the time evolution of CUSUM test.

5. Conclusion

In this paper, an approach was employed to monitor the operational modes of the distillation unit. This approach starts out with defining a NARMAX model for describing a normal behavior of a monitored process. Then by means of a CUSUM test when the residual of NARMAX model exceeds the predetermined threshold, the process is determined to be in abnormal state. Experimental results are also presented that verify the performance of the proposed techniques.

In this work, the proposed FD approach presents a greater detection delay. Consequently, other FD approaches based on experimental measurements is an interesting subject for future work for early detection of abnormalities in dynamic processes.

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