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Hybrid Fault Detection Method for a Distillation Unit

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Fault detection and isolation have become increasingly important problems over time, due to the more complex and larger scale industrial systems. The last few decades have seen a rise in research focused on developing robust and sensitive fault detection methods. Approaches using mathematical models, qualitative logic or operation data driven solutions were developed and while they all performed well overall some lacked in robustness and others in flexibility or sensitivity. In this study a hybrid fault detection approach using both parity relation methods and a Fuzzy Expert System (FES) to analyse and detect process faults in a distillation unit is introduced. The combination of the two schemes was used to handle the detection and classification of additive and multiplicative faults. The effectiveness of the hybrid method in alleviating the shortcomings of the single techniques has been verified by simulation and experimental tests.

1. Introduction

Parallel to the evolution of technological processes the demand for process safety has become a cardinal issue. In response Fault Detection and Isolation (FDI) techniques have become focal points of research. A fault as described by Venkatasubramanian et al. (2003) is an event when the variables of a process deviate from their normal values. FDI focuses on using knowledge about a system to analyse fault signatures and pinpoint the root cause behind the faults (Venkatasubramanian et al., 2003). Methods using quantitative system models for fault detection have been popularized and widely researched. A favoured technique based on these models is the parity relations technique (Arunthavanathan et al., 2021). Parity relations observe differences between idealized and actual system responses through the use of a model and subject them to a linear transformation to generate residuals characteristic of process faults. In recent years interest has shifted towards developing parity relations for non-linear systems and hybrid methods in contrast to the traditional linear models (Arunthavanathan et al., 2021). Hilbert et al. (2013) utilized residual based fault detection for analysing possible malfunctions in wind turbine systems. Jiang et al. (2020) investigated the possibilities for optimizing the residual generation process and to extend the parity relations approach to non-linear systems through the use of data-based techniques. Wan et al. (2020) combined the parity relations technique with statistic methods to identify parametric faults within systems based on a priori knowledge about their possibility of occurrence. Cho and Jiang (2019) utilized stochastic methods to enhance parity equation based residual generation. They investigated a statistical decision-making scheme for the FDI process where they focused on identification methods for the multivariate probability distribution functions of the residual classes. Ghaniee and Aliyari (2018) generalized the linear parity space approach to non-linear systems through the use of Takagi-Sugeno fuzzy models. They validated their method during the investigation of a mass-spring-damper system. Parametric uncertainties and faults modify the behaviour of the system itself rather than acting as additive inputs to the system. In the traditional framework (Safaeipour et al., 2021) parametric faults were associated with underlying parameters of the process and their presence could be detected with schemes derived from parameter identification. This approach while sensitive and accurate is more complex than the framework for handling additive faults. To alleviate this issue a new method is proposed in this paper which combines the parity relations approach with an expert system to detect additive and parametric faults within a distillation unit. The scheme was designed with the goal of creating a framework for the integration of empirical knowledge about the system to effectively and simply diagnose parametric faults.

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2. The experimental apparatus and process simulator

For demonstrating the operation of the proposed algorithm possible faults of a laboratory scale distillation unit were investigated. The physical system was modelled using Aspen HYSYS V11 (AspenTech, 2018). The dynamics of the column have been used to validate the HYSYS model and conduct further investigations. The layout of the laboratory unit can be seen in Figure 1a, a photograph of the physical system is added in Figure 1b.

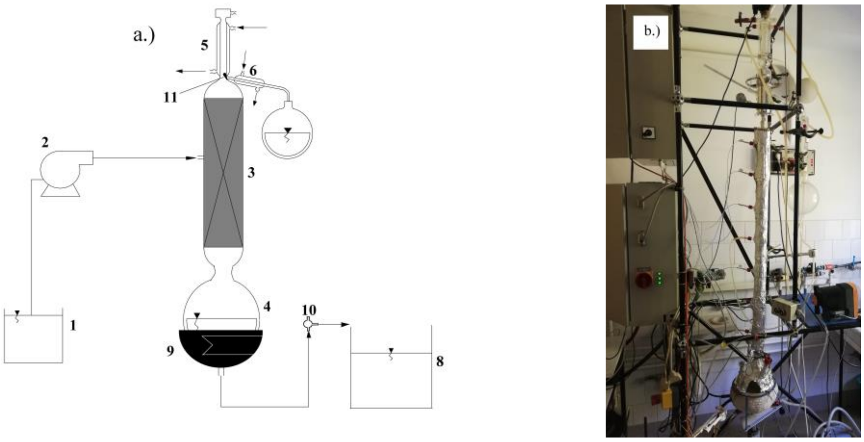

Figure 1: Layout of the investigated distillation unit (a), view of the physical system (b)

In this study the unit was investigated during the separation of a 18 wt% ethanol-water mixture. The mixture was stored in a feed tank (1) and transported into the column through a feed pump (2). The glass column consisted of four main parts: the column body (3), which was filled with Dixon rings as random packing, a three-neck flask which served as the reboiler (4) and the condenser (5) consisting of a spiral cooler and an additional cooler for sub-cooling the distillate (6). The distillate was collected in a round-bottom flask (7), while the bottoms product was collected in a bottom storage tank (8). The reboiler duty was controlled through the use of an electric heating mantle (9). The liquid level within the reboiler was controlled through the use of a three-way glass valve (10). Finally, the reflux ratio was controlled through the use of an electrically controlled valve (11). The valve was placed in front of the sub-cooler entrance. Table 1 displays the main constructional parameters of the unit, while Table 2 shows the operational parameters within the desired steady state.

Table 1: Constructional parameters of the column

Number of equilibrium stages (-)	Column diameter (m)	Column height (m)	Packing	Column material	Reboiler volume (L)
6	0.05	1.2	Dixon ring (1/8")	Glass	4

Table 2: Operational parameters of the column within the desired steady state

Inlet ethanol content (wt%)	Reboiler duty (W)	Reflux ratio	Inlet flow (L/h)	Distillate flow (L/h)	Bottoms flow (L/h)
18	200	0.36	1	0.288	0.712

The dynamic behaviour of the unit was investigated during a batch experiment. The reboiler was filled with the mixture and after heating the steady state temperature profile (T) within the unit has been observed with total reflux and zero bottom product flow rate. The temperature was measured using Pt-100 resistance thermometers and collected using the ADAMView software through the Adam-4000 I/O module.
Figure 2 displays the temperature profiles in the reboiler (T_r) and the top tray of the column (T_1) during the batch process for experimental (a) and simulation data in Aspen HYSYS (b) as a function of time (t). After the temperature within the reboiler reaches the boiling point the steam heats up the subsequent trays and gradually the vapor-liquid equilibrium becomes established. In case of experimental data for T_1 a zoom-in of the temperature profile was also provided since the heating up of the tray happens rapidly (0.01 h) and it might seem like the change in temperature is instantaneous. The difference of estimated time of the heat up between the simulated and modelled results was 0.04 h which is a relative error of 8 % compared to the total

heat up time obtained from simulation. Based on the results the HYSYS simulator was appropriate for analysing the dynamic behaviour of the unit near its steady state operation point established in Table 1.

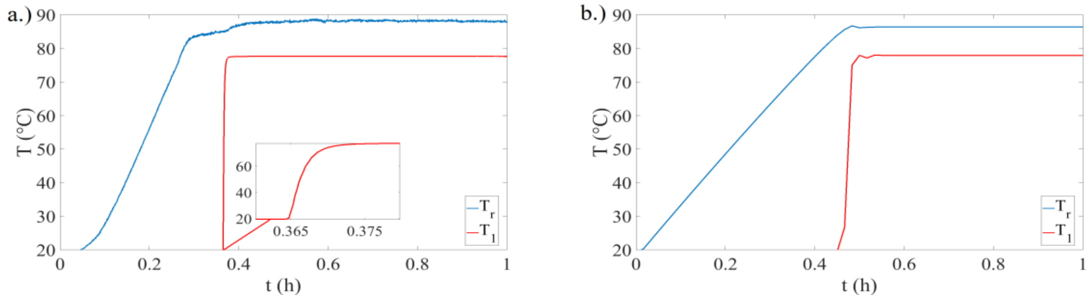

Figure 2: Temperature profiles according to experimental (a) and simulated data (b)

3. Modelling Results

Using the HYSYS simulator investigations were carried out to create a linearized State-Space (SS) model of the system near its operating point with two arbitrary state variables (x). The chosen inputs (u) for observation were the inlet feed volumetric flow (B or u_1) and the inlet ethanol mass fraction (x_{in} or u_2). The observed outputs (y) contained the top stage temperature (T_1 or y_1) and the reboiler temperature (T_r or y_2). By observing Figure 2 it can be seen that the simulation was adequately accurate for the estimation of both variables and since these values determine the composition of the bottom and distillate products they are key variables from an operational perspective. Figure 3a shows the input data used for investigation, while Figure 3b shows the output data obtained from HYSYS and the fitted model data. The fit was satisfactory, with an average of 98 % fit to the simulated data. The fitting was conducted using MATLAB R2020b (MathWorks, 2020). The objective function of the fitting, which estimated the one-step ahead prediction error between simulated and modelled data was numerically minimized through use of the subspace Gauss-Newton least squares search.

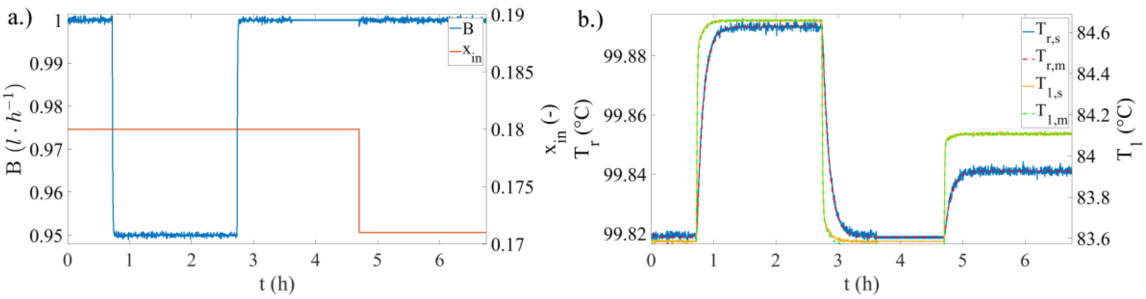

Figure 3: Input signal (a) with simulated and fitted response data (b), "s" and "m" indices refer to data obtained from HYSYS simulation and SS model respectively

The estimated, continuous SS model is displayed in Eq(1).

$$\begin{bmatrix} \dot{x}_1 \\ \dot{x}_2 \end{bmatrix} = \begin{bmatrix} -90.6 & -30.9 \\ -101.8 & -48.1 \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \end{bmatrix} + \begin{bmatrix} -3032 & -1054 \\ -3517 & -1161 \end{bmatrix} \begin{bmatrix} u_1 \\ u_2 \end{bmatrix}$$
$$\begin{bmatrix} y_1 \\ y_2 \end{bmatrix} = \begin{bmatrix} 0.10 & -0.09 \\ 1.85 & 0.43 \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \end{bmatrix} + \begin{bmatrix} 0 & 0 \\ 0 & 0 \end{bmatrix} \begin{bmatrix} u_1 \\ u_2 \end{bmatrix} \tag{1}$$

Parity relations for the system were estimated (Arunthavanathan et al., 2021). The system model was converted from continuous time to a discrete form. The response of the system was estimated in a moving window with width λ. Following this procedure the system response over the time window (Y) is calculated from Eq(2).

$$\bar{\bar{Y}}(t) = \bar{\bar{J}}\bar{x}(t-\lambda) + \bar{\bar{K}}\bar{\bar{U}}(t) + \bar{\bar{L}}_F\bar{\bar{F}}(t) \tag{2}$$

Eq(2) describes the output over the time window which can be estimated from the initial state of the system ($x(t\text{-}\lambda)$), the input evolution matrix (U) and the fault evolution over the window (F). The equation also contains parameter matrices J, L_F and K derived from the SS model. Two types of additive faults were considered, one being a fault in the input volumetric flow sensor the other being a fault in the input composition sensor. The faults directly affect the input signals. Their parameter matrices within the SS model were assumed to be the same as the input parameter matrix. A general residual generator was established for this fault detection problem with a form shown in Eq(3).

$$\bar{r}(t) = \bar{\bar{W}}\left(\bar{\bar{Y}}(t) - \bar{\bar{K}}\bar{\bar{U}}(t)\right), \qquad where\ \bar{\bar{W}}\bar{\bar{J}} = \bar{\bar{0}} \tag{3}$$

In Eq(3) W represents the linear transformation of residual (r) generation which is defined so that the achieved residuals allow clear distinctions between faults and the linear transformation decouples the residuals from the state variables ($WJ=0$). For this FDI problem a set of two diagonal residuals was designed where each residual (r_1, r_2) only responds to a single specific fault. The data used for testing the residual generator is shown in Figure 4.

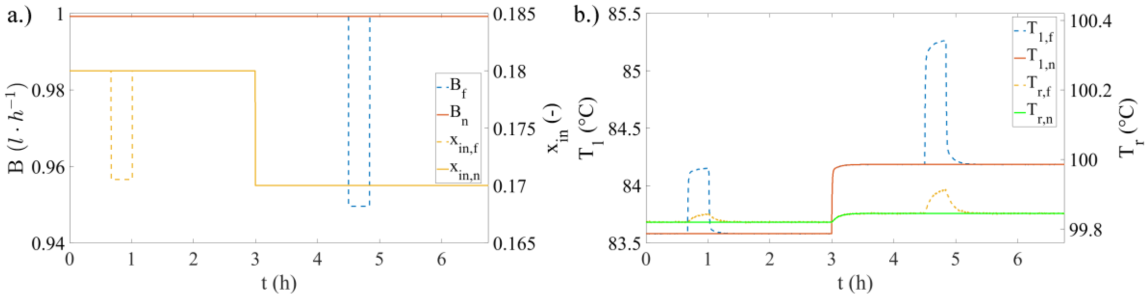

Figure 4: Normal and faulty input signals (a) and normal and faulty responses (b), with indices "f" and "n" referring to data variables under faulty and normal conditions

The data contains noise from the process which creates difficulties for residual generation.
A transformation was developed to extract clear residual signatures from the noisy data. The transformed signal (m) is calculated according to Eq(4).

$$m(\delta,\omega) = \frac{p_1 E(r_{\delta,\omega})}{p_2 V(r_{\delta,\omega}) + p_3}, \qquad where\ p_2, p_3 > 0 \tag{4}$$

The transformation operates like a moving average filter with window width ω. For each residual value at a discrete time δ the average of the residual across the window ($E(r_{\delta,\omega})$) is divided by the variance of the sample across the window ($V(r_{\delta,\omega})$). The parameters p_1, p_2, p_3 are for weighting. The residual signals obtained from noisy data and the transformed residuals can be seen in Figure 5. For the transformation ω=50, p_1=10, p_2=5 and p_3=0.1 parameters were utilized.
Figure 5 showcases the strength of the process with clearly developed transformed residuals (m_1, m_2) indicative of the presence of faults when compared with Figure 4.

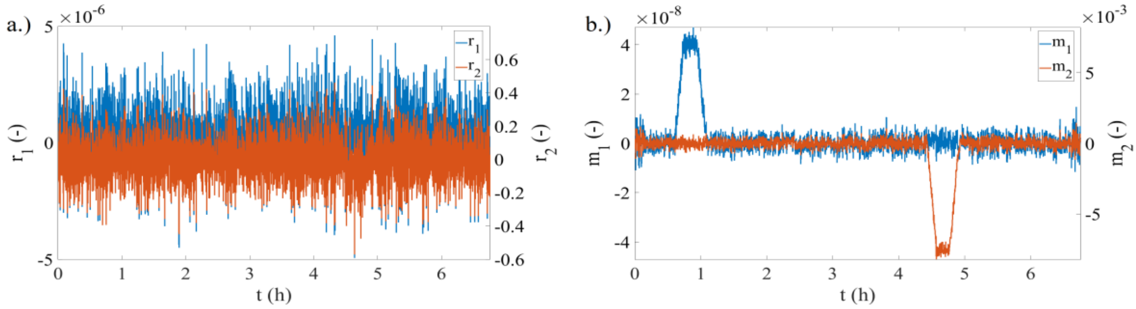

Figure 5: Obtained, noisy residual signal (a) and transformed residual signal (b)

Parametric faults, differently to additive faults are usually a result of internal damage and aging of the system, which changes the mathematical model of the system itself. These processes including corrosion, fouling, etc. are usually slow and result in a gradual deviation of the process from its normal state rather than an abrupt change. To showcase the method used for detecting these abnormalities heat exchanger fouling within the reboiler has been introduced as a parametric fault. Heat exchanger fouling was introduced into the HYSYS simulation by decreasing the duty of the heat exchanger (Q) according to Eq(5).

$$Q = Q_0 - \rho t \quad (5)$$

The fouling was assumed to be a linear function of time where Q_0 represents the initial steady-state duty within the reboiler and ρ is the rate of fouling, in this case 0.3 W/h. After obtaining simulation results for the process behaviour with fouling residuals were generated. The system response and transformed residuals are displayed in Figure 6. Due to the fouling a slow, gradual change in temperature and the residual values can be noticed.

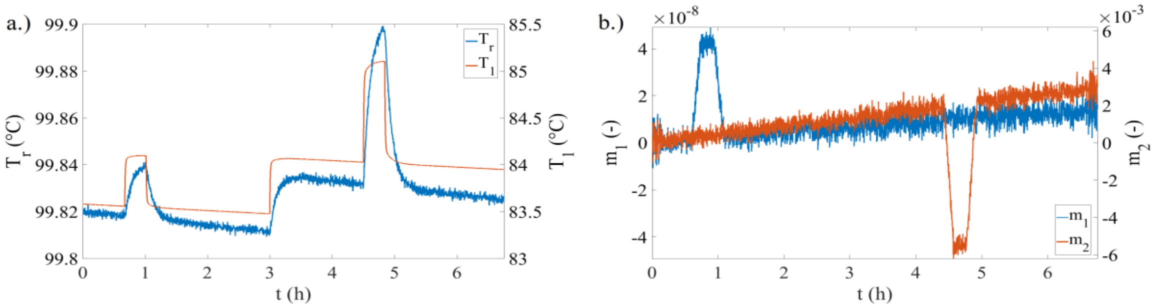

Figure 6: System response (a) and transformed residual signal with fouling (b)

To detect heat exchanger fouling within the reboiler a FES was established and optimized manually. In accordance with Eq(3) residual signals are linear transformations of the difference between actual system outputs (in this case reboiler and top tray temperatures) and outputs calculated based on the system model. The reboiler and top temperature are highly sensitive to the reboiler duty and fouling the residuals obtained through their linear transformations hold the same characteristics. To provide an input for the FES a new measure was introduced according to Eq(6).

$$M(\delta,\omega) = \begin{cases} \prod_{i=1}^{2} \min\left(\frac{m_i(\delta,\omega)}{max(|m_i|)}\right), if\ max(|m_i|) > 0 \\ 0, \qquad else \end{cases} \quad (6)$$

The measure (M) in Eq(6) utilizes the relative value of the transformed residuals compared to their maximum value over the entire time window. The minimum of this value is evaluated over a moving window with length ω and the value of the obtained measure within each discrete sampling time δ is calculated as the product of the values for all residuals affected by parametric faults. Using the measure as a fuzzy input FES membership functions were established and optimized. The crisp input M was converted into the corresponding linguistic variables “low” and “high” to characterize the measure. If the qualitative value of the measure is high then the likelihood of fouling within the reboiler which is the output of the FES is also high. Fuzzy Membership Functions (*mf*) for both inputs and outputs were chosen to be sigmoidal functions. The general form of the mf is shown in Eq(7). The constant parameters (*a*, *b*) for this investigation have been adjusted manually and are displayed in Table 3.

$$mf(a,b) = \begin{cases} \frac{1}{1+e^{-\left(\frac{M-b}{a}\right)}}, for\ increasing\ values \\ 1 - \frac{1}{1+e^{-\left(\frac{m_{f,1}-b}{a}\right)}}, for\ decreasing\ values \end{cases} \quad (7)$$

Table 3: Constructional and operational parameters of the column for the desired steady state

	Type	a	b	Type	a	b
Input membership functions	“Low” function	$8\cdot10^{-3}$	$5\cdot10^{-3}$	“High” function	$8\cdot10^{-3}$	0.02
Output membership functions	“Low” function	0.03	0.25	“High” function	0.05	0.4

The obtained measure with a window range of 300 samples and the probability of heat exchanger fouling (*P*) within the reboiler obtained through fuzzy logic are displayed in Figure 7a and b.

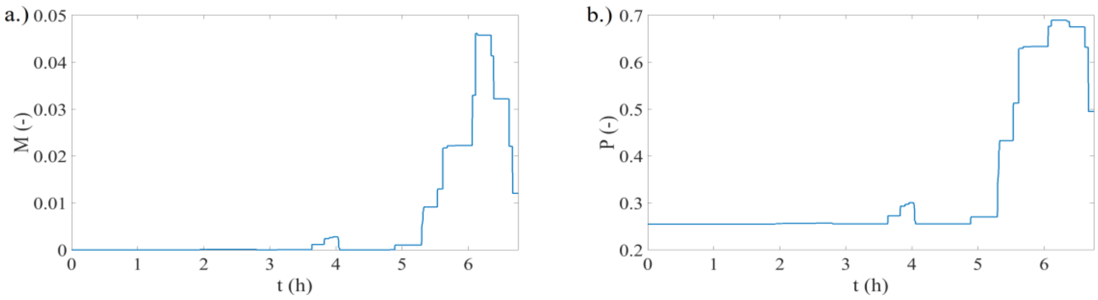

Figure 7: The generated measure (a) and the probability of fouling obtained from fuzzy logic (b)

The figure shows that the measure successfully decoupled signals of fouling from additive faults and provided a basis for the analysis of fouling using fuzzy logic. In case of multiple parametric faults gains on the individual filtered residual signals can be adjusted to enable characteristic signal development. Additionally, the values of the filtered residuals can also be used for analysis through fuzzy logic.

4. Conclusions

During the course of this study an FDI procedure was developed for a distillation column using both experimental results and process simulators (Aspen HYSYS). The traditional parity relations method combined with fuzzy logic was used as a basis for fault detection. A novel transformation method, useful for enhancing residual signals and decoupling them from noise (Figure 5) has been proposed; and a measure has been derived for decoupling additive and parametric faults. The derived method is robust and capable of sensing the presence of parametric faults and decoupling them from additive faults. In case of heat exchanger fouling the method was sensitive enough to recognize the presence of fouling after 5.23 h at a decrease of 1.57 W in inlet heat exchanger duty. This is a deviation of only 0.78 % from the original steady-state duty (Table 2), all in the presence of process noise.

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