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Diagnosis and on-line parametric estimation of simulated moving bed

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Abstract— **In this paper, a recently developed graphical signatures generation tool is used for diagnosis and on-line parametric estimation of simulated moving bed (SMB). The underlying diagnosis problem corresponds to variations affecting four of system's parameters, namely, the two Langmuir coefficients, the extract and the feed flow rates. It is shown that this diagnosis method enables detection, isolation and parameter estimation even under simultaneous faults. Comparison with a simple least squares approach shows that the proposed approach needs drastically less iterations and therefore corresponds to a fast estimation results.**

keywords: Diagnosis, parameters estimation, nonlinear dynamics, signature generation, multiple faults.

I. INTRODUCTION

The Simulated-Moving-Bed (SMB) is an efficient counter-current separation process that is extensively used in the process industry. The SMB has been studied in the literature concerning different aspects including design, modelling and simulation [3], [5], optimization for selection of optimal operating conditions and respect of operating constraints, control [9], [4] and state observers design [1]. All these studies clearly show that the performances of a high separation **SMB** are extremely sensitive to variations in the system's parameters. Consequently, model based approaches in control as well as in state observer design need a very good knowledge of these parameters. Key parameters in **SMB** are the isotherm coefficients and the flow rates realized at the input and output ports. Monitoring variations and/or fault affecting these parameters is linked to what is commonly known as fault detection and isolation or more shortly, on line diagnosis.

Diagnosis includes fault detection and isolation (FDI). By fault detection, one means that a faulty behaviour symptoms have been detected while isolation amounts to identify the precise fault configuration leading to these symptoms. Various approaches have been proposed for the design of FDI algorithms in the literature. Among them, the observer based methods [12], [7].Analytical redundancy can also be used in an algebraic framework in order to detect variations on parameters [11], [6]. Fuzzy logic-based schemes may be invoked through parity equations [8]. Statistical and local approaches based on signal processing and statistical properties monitoring have been proposed [2], [15] as well as methods based on the wavelets transformation [10] that can generically be applied to detect singular behaviors based on the spectral content of the measured signals.

In the present paper, a recently developed [13], [14] signature-based methodology is used to derive a diagnosis tool for the Simulated Moving Bed. The signature based methodology proposed in [13], [14] uses a general signature generation algorithm to yield a diagnosis procedure by means of the following three steps :

Step 1: Generating signatures. In this first step, a family of $2D$ graphical signatures is generated for nominal and faulty configurations. This is done using the physical simulation model in which variations on the parameters are introduced. Furthermore, several parameterizations of the signature generation tool are used in order to enhance detection and isolation capacity.

Step 2: Signature analysis. In this second step, the high classification ability of human brain is used to analyse the signatures produced in the first step. The way variations on parameters induce signature deformations is analyzed in order to define relevant GEOMETRICAL residuals. This step may invoke the first one in order to produce additional signatures enabling detection and isolation to be performed.

Step 3: Definition of mathematical residuals. Once a relevant set of geometrical residuals is defined in Step 2. A mathematical translation is then performed in order to derive mathematical residuals that can be used in an on-line diagnosis framework.

The above three-steps diagnosis design strategy is applied in this paper to yield a diagnosis algorithm for the simulated moving bed **SMB** diagnosis problem.

The paper is organized as follows. The **SMB** system model is presented in section II and the diagnosis problem under interest is clearly stated. Section III recalls the technique based on graphical signature [13] for the fault detection and isolation of dynamical systems which is used. Application of this methodology to the **SMB** diagnosis problem is presented in section IV. Section V shows how one can estimate the values of parameters using an automatic on-line SMB parametric estimation. A comparison with a simple least squares approach is done in Section VI. The paper ends with a conclusion.

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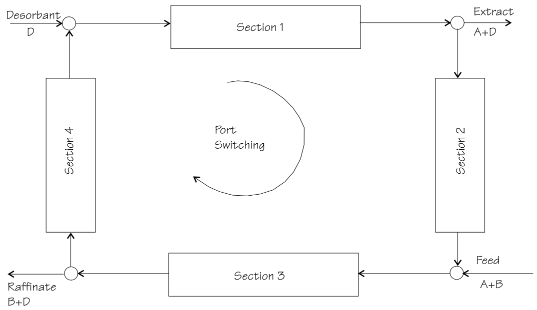

Fig. 1. Schematic view of a simulated moving bed

II. THE SIMULATED MOVING BED DIAGNOSIS PROBLEM

A simulated-moving-bed (**SMB**) chromatographic system (see Figure 1) is obtained by connecting several single chromatographic columns in series to form four functional sections. A countercurrent movement of the bed is simulated by periodically switching the inlet and outlet ports in the direction of the fluid stream. The aim of the whole system is to separate the components A and B initially present in the inlet feed stream. In the case of the SMB shown in Figure 1, component A is recovered at the outlet of section 1 while component B is recovered at the outlet of section 3. The flow rates of the fluid stream in the different four sections can be controlled by varying the four independent flow rates: recycle, extract, raffinate and desorbent. Assuming a fast transfer of species A and B between the two phases, the system behaviour in each section may be described by the following PDE's

$$\frac{\partial}{\partial t}\begin{pmatrix} c_A \\ c_B \end{pmatrix} = Q(c_A, c_B)\Big[D_{ax}(u)\frac{\partial^2}{\partial x^2}\begin{pmatrix} c_A \\ c_B \end{pmatrix} - u\frac{\partial}{\partial x}\begin{pmatrix} c_A \\ c_B \end{pmatrix}\Big] \quad (1)$$

where c_A, c_B are the concentrations of components A and B respectively and u is the fluid velocity in the considered section. Therefore, four velocities u_i's are to be considered that can be computed from the four flow rates at inlet/outlet ports using classical incompressibility assumption. $D_{ax}(u)$ is the diffusion coefficient while the matrix $Q(c_A, c_B) \in \mathbb{R}^{2\times 2}$ is given by

$$Q(c_A, c_B) := \begin{pmatrix} 1 + \frac{1-\varepsilon}{\varepsilon}\frac{\partial q_A^{eq}(c)}{\partial c_A} & \frac{1-\varepsilon}{\varepsilon}\frac{\partial q_A^{eq}(c)}{\partial c_B} \\ \frac{1-\varepsilon}{\varepsilon}\frac{\partial q_B^{eq}(c)}{\partial c_A} & 1 + \frac{1-\varepsilon}{\varepsilon}\frac{\partial q_B^{eq}(c)}{\partial c_B} \end{pmatrix}^{-1}$$

where $q_j^{eq}(c_A, c_B)$ expresses the Langmuir competitive isotherm given by :

$$q_j^{eq}(c_A, c_B) := \frac{K_j c_j}{1 + K_A c_A + K_B c_B} \quad ; \quad j \in \{A, B\} \quad (2)$$

Different isotherms can be used according to the components to be separated, however, the competitive Langmuir isotherm is a quite general and efficient law that can be used to model the separation of many multivariate mixtures.

The performances of the Simulated Moving Bed are very sensitive to variations on K_A, K_B and to errors (offset, drift) on the inlet/outlet flow rates. In this paper, a recently developed signature based diagnosis tool [13] is applied to detect and isolate even simultaneous variations on the Langmuir coefficients K_A, K_B and the feed and extract flow rate q_{feed} and q_{ext}. This is done using a vector y_m of some measured outputs, namely, the concentrations of the components A, and B at the inlet and outlet ports:

$$y_m = \begin{pmatrix} y_1 & y_2 & y_3 & y_4 \end{pmatrix} \quad (3)$$

y_1, y_2 are the concentrations (at the extract) of components A and B respectively. y_3 is the concentration of component A at the feed while y_4 is the concentration of component B at the desorbent inlet port.

The **SMB** diagnosis problem considered in the present paper may be stated as follows: Design an algorithm that uses the measurements vector (3) to detect and isolate any even simultaneous variations in the parameter vector

$$\begin{pmatrix} K_B & K_A & q_{ext} & q_{feed} \end{pmatrix} \in \mathcal{K} \subset \mathbb{R}^4$$

where $\mathcal{K}$ is a domain of interest containing realistic values of the above parameters.

It goes without saying that the problem at hand can a priori be solved using least squares optimisation, namely, by finding the parameter values that minimise the integral of the squared measurement prediction error over the admissible domain. It has been shown however that the graphical residual definition step performed by the human eye in the first step defined above leads to a kind of decoupling or "*co-ordinate change*" that makes the signature based diagnosis more efficient than simple least squares methods in terms of the number of iterations needed to obtain a good solution. Comparisons are given in section VI to assess this claim.

Since in each iteration, the system has to be simulated over a long time horizon, reducing the number of iterations automatically leads to shorter response time. This feature enabled an on-line application of the signature based methodology to the problem of diagnosis and parameter estimation of an automotive electronic throttle control system [14]. The aim of the present paper is to show that the same generic methodology applies to the SMB diagnosis problem defined above.

III. DIAGNOSIS BY GRAPHICAL SIGNATURE

The starting point of this method is the known fact that "*human eyes through the underlying brain activity*" is able to accomplish high complexity classification tasks. This high classification ability needs however to be applied to some pattern. The aim of this method is to propose output-measurement-based generated patterns that are called signatures. More precisely a map from a high dimensional space to which belong the vector of past measurements over some moving time-window to $\mathbb{R}^2$ is defined. When applying this map to a moving-horizon past measurements, one obtains a bi-dimensional curve. Now, if for each faulty scenario, the "*corresponding signature*" differs from the nominal one in a distinguishably different way, from a human eye "*viewpoint*" then the graphical tool may be used in the context of fault detection and even isolation under certain assumptions. In order to clearly summarize the signature generation algorithm proposed in [13] and used hereafter to solve the **SMB** diagnosis problem, some definitions and notations are needed. This is the aim of the following section.

A. Some definitions and notations

The definitions given here refer to the case of one-dimensional output measurement. To this respect, each of the four components of y_m given by (3) is used to generate a different signature.

1) The normalization function N_ε:
Consider a scalar output y that is measured with some sampling rate. The vector of past measurements $y(t_1),\ldots,y(t_N)$ is then used to construct a measurement vector Y. A normalization map is then applied to Y in order to obtain components that lie in $[-1,1]$, namely

$$N_\varepsilon : \mathbb{R}^N \to \mathbb{R}^N \; ; \; N_\varepsilon(Y) = \bar{Y} = \frac{Y}{\|Y\|_\infty + \varepsilon} \qquad (4)$$

where $\varepsilon > 0$ is some small regularizing coefficient while $\|Y\|_\infty$ is given by: $\|Y\|_\infty = max|Y_i|_{i=1}^N$

2) Definition of a pencil P_ε:
A pencil is a map $P_\varepsilon : \mathbb{R}^N \times \mathbb{R} \to \mathbb{R}^2$ that associates to each element (Y,y) of $\mathbb{R}^N \times \mathbb{R}$ (a set of $N+1$ measurements) a point in the bi-dimensional plane:

$$P_\varepsilon : \mathbb{R}^N \times \mathbb{R} \to \mathbb{R}^2$$
$$(Y,y) \to \Phi_0(\bar{Y}) + \lambda_\varepsilon(\bar{Y},y)[\Phi_1(\bar{Y}) - \Phi_0(\bar{Y})]$$

where: $\lambda_\varepsilon(\bar{Y},y) = \frac{y}{\|\bar{Y}\|_\infty+\varepsilon} - \frac{1}{N}\sum_{i=1}^N \bar{Y}_i$,

$$\Phi_0(\bar{Y}) = \tfrac{1}{N}\sum_{j=1}^N \Psi_j(\bar{Y}); \Phi_1(\bar{Y}) = \tfrac{1}{N}\sum_{j=1}^N \bar{Y}_j \Psi_j(\bar{Y}),$$

$$\Psi_i(\bar{Y}) = \tfrac{1}{2}[(1+\bar{Y}_i)Q_{(i+1|N)} - (\bar{Y}_i - 1)Q_i],$$

$$Q_i : image(e^{2j(i-1)\frac{\pi}{N}}) \quad ; \quad j^2 = -1.$$

$(Q_i)_{i=1}^N$ are the N nodes of a regular N-dimensional polygone in $\mathbb{R}^2$, $(i+1|N) = (i+1)Modulo\ N$. Note that $\Phi_0(\cdot)$ and $\Phi_1(\cdot)$ clearly define two points in the two-dimensional plan that are respectively the non weighted center of mass of the $\Psi_i(\bar{Y})$ and the weighted c.o.m with Y_i as weights. $P_\varepsilon(Y,y)$ is a point on the line $\overrightarrow{\Phi_0\Phi_1}$ with relative position defined by y. See [13] for more details.

B. Dynamical signature generation

Let us denote by δ the sampling time for measurements acquisition and define the following vector:

$$Y(t,N) = [y(t-N\delta),\ldots,y(t-\delta)]^T \in \mathbb{R}^N \qquad (5)$$

Using a moving window of width N from measurements $[y(t-i\delta)]_{i=0}^{m-1+N}$ and the pencil P_ε defined above, the following points in the 2D plane can be defined:

$$P_i(t,N) = P_\varepsilon\Big(Y(t-(i-1)\delta, N), \; y(t-(i-1)\delta)\Big) \; i = 1...m \qquad (6)$$

TABLE I

SMB SYSTEM FAULTS

DOMAINE OF VARIATIONS OF THE PARAMETERS ($\mathcal{K}$).

No.	Description	Parameter	Interval
1	Langmuir coefficient	K_B	[2 2.4]
2	Langmuir coefficient	K_A	[1.5 2]
3	Extract flow rate	q_{ext}	$[7.51\times10^{-5} \;\; 9.02\times10^{-5}]$
4	Feed flow rate	q_{feed}	$[0.56\times10^{-5} \;\; 0.68\times10^{-5}]$

$(P_i(t,N))_{i=1}^m$ define m points in R^2 which constitute the two-dimensional signature $S_\varepsilon(t,N)$ at time t. Analytically, $S_\varepsilon(t,N)$ can be written as follow: $S_\varepsilon(t,N) = (S_\varepsilon^x, S_\varepsilon^y)$ where $S_\varepsilon^x = \big(P_1^x(t,N)...P_m^x(t,N)\big)^T$ and $S_\varepsilon^y = \big(P_1^y(t,N)...P_m^y(t,N)\big)^T$. Note that Different signatures can be obtained by modifying the value of N which will be called signature order.

IV. APPLICATION TO THE SIMULATED MOVING BED

In this section, the signature generation tool is used to solve the SMB diagnosis problem stated in section II. According to the definition of the signature, one degree of freedom can be modified to be useful in diagnosis, namely, the signature order N. By taking 80 measurements of y_1, y_2, y_3 and y_4 with a sampling period of $2s$ that is a moving window of $160s$, one generates four dynamical signatures: $S_1 = S_\varepsilon(t,20)$ generated from y_4 measurements, $S_2 = S_\varepsilon(t,36)$ generated from y_1 measurements, $S_3 = S_\varepsilon(t,15)$ generated from y_3 measurements and $S_4 = S_\varepsilon(t,5)$ (without normalisation, $\|Y\|_\infty = 1$) generated from y_2 measurements. Using these signatures, one could detect isolate and estimate all even simultaneous variations of the four considered parameters K_B, K_A, q_{ext} and q_{feed} within the prescribed regions given in table 1. As it is shown in the following section, SMB diagnosis is done in the following order: K_B, K_A and then q_{ext}, q_{feed}.

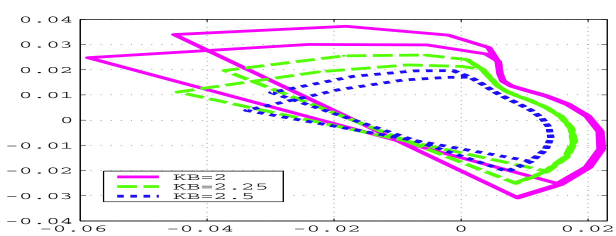

Fig. 2. Sensitivity of the signature S_1 to variations on K_B, $(K_A, q_{ext}, q_{feed}) = (1.5, 7.514\times10^{-5}, 0.562\times10^{-5})$.

A. Detection of variations on K_B

The *allure* of the signature S_1 in the case of variations affecting K_B under nominal values of (K_A, q_{ext}, q_{feed}) is illustrated on figure 2. It is easy to notice that when K_B decreases, the *allure* of the signature S_1 lengthens. Now, the interesting question is: How does this property (residual ...?) changes when the other parameters vary ?

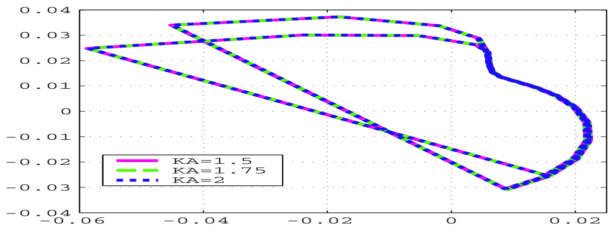

Fig. 3. The signature S_1 is insensitive to variations on K_A, $(K_B, q_{ext}, q_{feed}) = (2, 7.514 \times 10^{-5}, 0.562 \times 10^{-5})$.

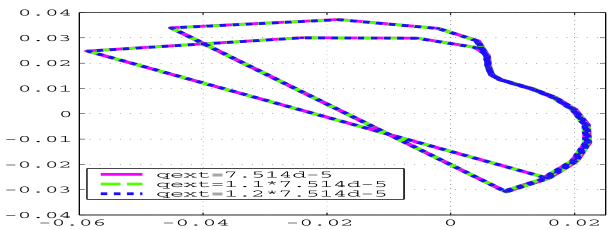

Fig. 4. The signature S_1 is insensitive to variations on q_{ext}, $(K_B, K_A, q_{feed}) = (2, 1.5, 0.562 \times 10^{-5})$.

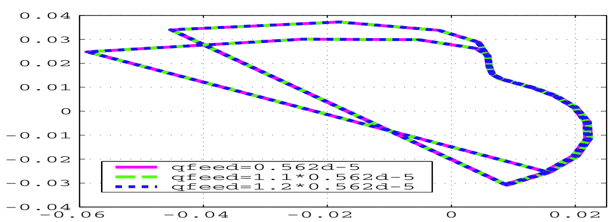

Fig. 5. The signature S_1 is insensitive to variations on q_{feed}, $(K_B, K_A, q_{ext}) = (2, 1.5, 7.514 \times 10^{-5})$.

Figures 3,4, 5 show that the signature S_1 is insensitive to variations on the other parameters, thus one can use this signature to detect, isolate and estimate variations on K_B without knowing the other parameters. Note that interesting points of S_1 are clearly those corresponding to minimal or maximal values for x-coordinate. Consequently the mathematical, say residual r_{kb} which allows us to detect, isolate and estimate variations on K_B can be written as follow:

$$r_{kb}(t) = min[S_1^x] \quad (or \quad r_{kb}(t) = max[S_1^x]).$$

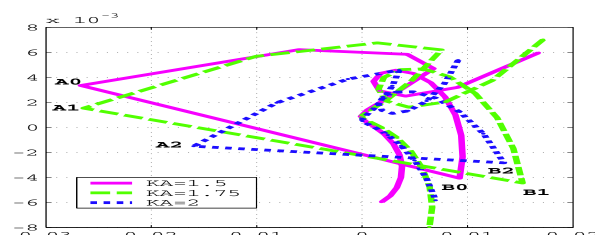

Fig. 6. Sensitivity of the signature S_2 to variations on K_A, $(K_B, q_{ext}, q_{feed}) = (2, 7.514 \times 10^{-5}, 0.562 \times 10^{-5})$.

B. Detection of variations on K_A

The *allure* of the signature S_2 in the case of variations affecting K_A under nominal values of (K_B, q_{ext}, q_{feed}) is

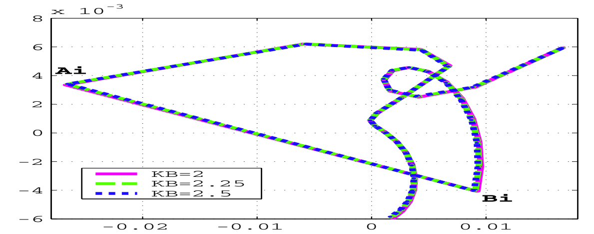

Fig. 7. The slope of the lines A_iB_i of the signature S_2 is insensitive to variations on K_B, $(K_A, q_{ext}, q_{feed}) = (1.5, 7.514 \times 10^{-5}, 0.562 \times 10^{-5})$.

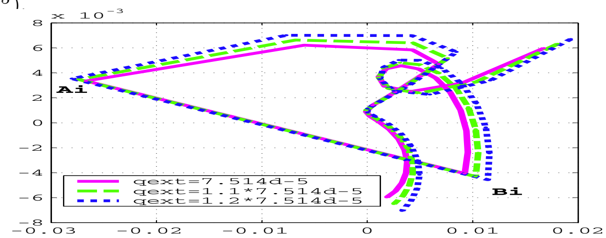

Fig. 8. The slope of the lines A_iB_i of the signature S_2 is insensitive to variations on q_{ext}, $(K_B, K_A, q_{feed}) = (2, 1.5, 0.562 \times 10^{-5})$.

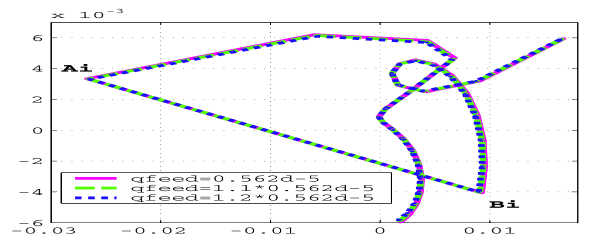

Fig. 9. The slope of the lines A_iB_i of the signature S_2 is insensitive to variations on q_{feed}, $(K_B, K_A, q_{ext}) = (2, 1.5, 7.514 \times 10^{-5})$.

illustrated on figure 6. It is clear that when K_A increases, the *slope* of the line A_iB_i of the signature S_2 decreases. Interesting points of S_2 are those corresponding to minimal values for x-coordinate (A_i) and those corresponding to maximal absolute values for second derivative $|\frac{d^2 S_2^y}{d S_2^{x\,2}}|$ such as $S_2^x > 0$ (B_i) and consequently K_A-estimation can be done using these points. Note that this property of S_2 is insensitive to variations on K_B, q_{ext} and q_{feed} (see figures 7,8,9). Thus one can use this signature to detect, isolate and estimate variations on K_A without knowing the value of (K_B, q_{ext}, q_{feed}). Consequently, residual r_{ka} which allows us to detect, isolate and estimate variations on K_A can be written as follow:

$$r_{ka}(t) = \frac{S_2^y(B) - S_2^y(A)}{S_2^x(B) - S_2^x(A)}$$

Where in the signature S_2, A is the point of minimal x-coordinate and B is the point of positive x-coordinate such as the absolute value for second derivative is maximum.

C. Detection of variations on q_{ext}

Figure 10 illustrates the *allure* of the signature S_3 in the case of variations affecting q_{ext} under nominal values of (K_B, K_A, q_{feed}). It is easy to notice that when q_{ext} increases, the signature S_3 lengthens. In this case, Interesting

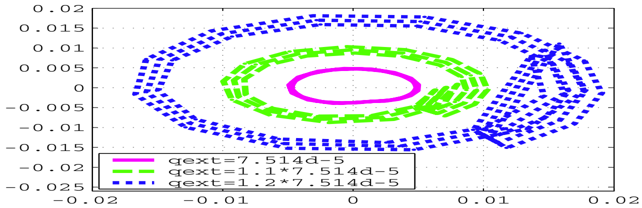

Fig. 10. Sensitivity of the signature S_3 to variations on q_{ext}, $(K_B, K_A, q_{feed}) = (2, 1.5, 0.562 \times 10^{-5})$.

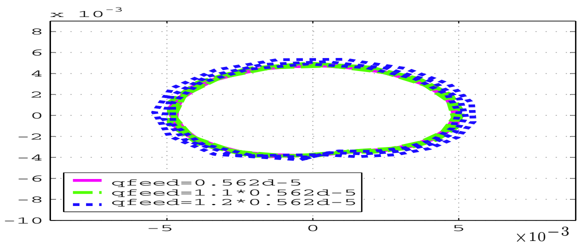

Fig. 11. The signature S_3 is insensitive to variations on q_{feed}, $(K_B, K_A, q_{ext}) = (2, 1.5, 7.514 \times 10^{-5})$.

points which allow us the estimation of q_{ext} are those of S_3 corresponding to maximal and minimal values for x-coordinate. Note that this property of S_3 remains valid for all admissible values of (K_B, K_A) and this signature is insensitive to variations on q_{feed} (see figure 11). Thus one can use this signature to detect, isolate and estimate variations on q_{ext} if the value of (K_B, K_A) is known and without knowing the value of q_{feed} . (K_B, K_A) can be estimated using the signatures S_1 and S_2. Consequently residual r_{qext} which allows us to detect, isolate and estimate variations on q_{ext} can be written as follows :

$$r_{qext}(t) = max[S_3^x] - min[S_3^x]$$

D. Detection of variations on q_{feed}

Figure 12 illustrates the *allure* of the signature S_4 in the case of variations affecting q_{feed} under nominal values of (K_B, K_A, q_{ext}). It is easy to notice that when q_{ext} increases, the allure of the signature S_4 lengthens to the right. Interesting points of S_4 are those corresponding to maximal values for x-coordinate and consequently q_{ext}-estimation can be done using these points. Note that this property of S_4 remains valid for all admissible values of (K_B, K_A, q_{ext}). Thus one can use this signature to detect, isolate and estimate variations on q_{feed} if the value of (K_B, K_A, q_{ext}) is known. (K_B, K_A, q_{ext}) can be estimated using the signatures S_1, S_2 and S_3 associated to the above sections. Consequently residual r_{qfeed} which allows us to detect, isolate and estimate variations on q_{feed} can be written as follow:
$r_{qfeed}(t) = max[S_4^x]$.

V. SMB PARAMETERS ESTIMATION

Based on the mathematical residuals defined above, the on-line SMB parameters estimation can be done using interpolation method. The value of estimated parameter can

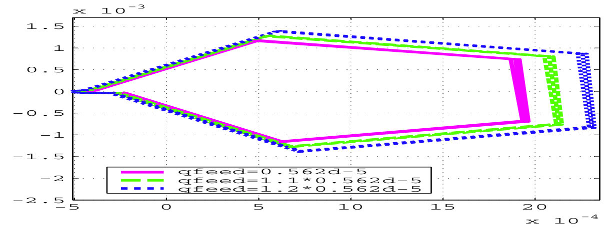

Fig. 12. Sensitivity of the signature S_4 to variations on q_{feed}, $(K_B, K_A, q_{ext}) = (2, 1.5, 7.514 \times 10^{-5})$.

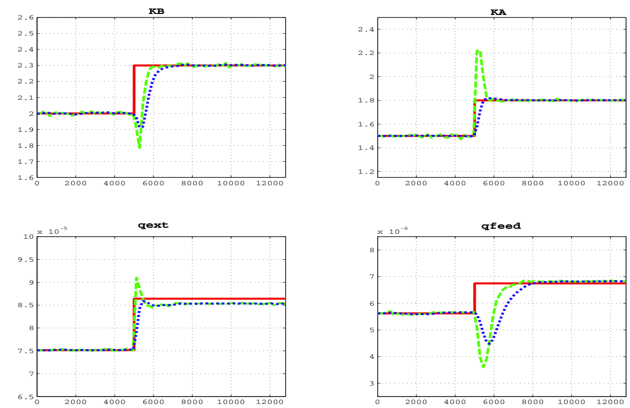

Fig. 13. On line SMB estimated parameters in the case of simultaneous change at t=5000s (real parameters: solide line '-', estimated parameters: dashed line '- -', estimated parameters after filtering: dotted line':').

be deduced from the corresponding residual value. Parameters estimation is done in the following order: K_B, K_A, q_{ext} and then q_{feed}. For instance the estimated q_{ext} given $\hat{K}_b$, $\hat{K}_a$ is the solution of $\varphi(q_{ext}, \hat{K}_b, \hat{K}_a, q_{feedn}) = measured\ [r_{qext}(t)]$ where $\varphi(\sigma, \hat{K}_b, \hat{K}_a, q_{feedn})$ is the residual $r_{qext}(t)$ computed with $q_{ext} = \sigma$, $(K_B, K_A) = (\hat{K}_b, \hat{K}_a)$ (estimated values) and $q_{feed} = q_{feedn}$ (nominal value). Figure 13 shows estimated parameters in the case of simultaneous parameters change at $t = 5000s$ from :

$$\begin{pmatrix} K_B \\ K_A \\ q_{ext} \\ q_{feed} \end{pmatrix} = P_0 = \begin{pmatrix} 2 \\ 1.5 \\ 7.514 \times 10^{-5} \\ 0.562 \times 10^{-5} \end{pmatrix}$$

$$to \quad \begin{pmatrix} K_B \\ K_A \\ q_{ext} \\ q_{feed} \end{pmatrix} = \begin{pmatrix} 1.15 & 0 & 0 & 0 \\ 0 & 1.2 & 0 & 0 \\ 0 & 0 & 1.15 & 0 \\ 0 & 0 & 0 & 1.2 \end{pmatrix} \times P_0$$

A 5% relative noise is added to measurements (see figure 14). Since all signatures and residuals are defined for a constant values of the parameters in a moving window of width $L = 160s$, signatures generated by a measurement window containing the step change are not relevant. For this reason estimated parameters are filtered by a low pass filter. Figures 15 shows estimated parameters in the case of two parameters change: (K_B, q_{feed}). It is clear that one can consider the difference between estimated parameters and nominal parameters as residuals which allow us to detect and isolate all considered parameters variations. In practice,

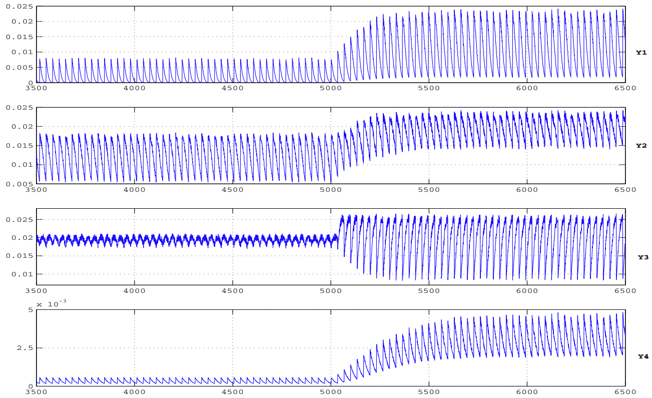

Fig. 14. Measurements with simultaneous parameters change at t=5000s.

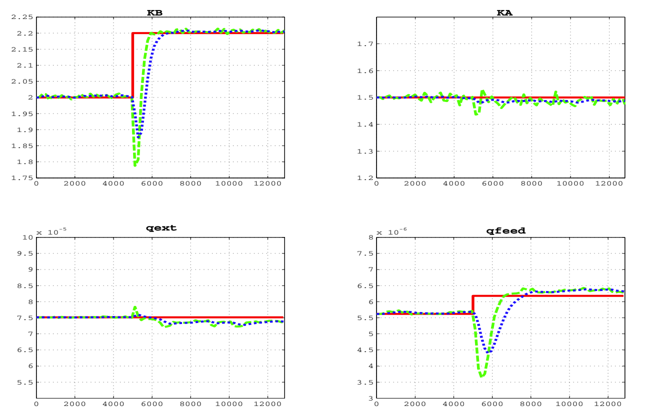

Fig. 15. On line SMB estimated parameters in the case of simultaneous change in (K_B, q_{feed}) at t=5000s (real parameters: solide line '-', estimated parameters: dashed line '- -', estimated parameters after filtering: dotted line':').

due the noisy measurement, a residual is never completely vanishing even when the corresponding parameter is not faulty (see for instance figures 15), therefore, a thresholds should be used in the decision unity. The definition of such threshold is in itself an active research area in the diagnosis community and is not handled in the present paper.

VI. Comparison with least squares approach

The least squares estimation approach looks for the parameter vector that minimizes the integral of the squared output prediction error. Note that the two approaches invoke as the key task, the integration system model over some prediction horizon in order to perform computation (residual evaluation for the signature-based approach and the cost function evaluation for a candidate vector for the least squares approach).

To this respect, note that the signature based approach needs 6 **iterations** to perform a very good estimation (the one given in the above figures). This is because the estimation of the Langmuir coefficients K_A and K_B needs no iterations while three simulations are needed for q_{ext} and q_{feed} respectively. Note that this is valid over the whole range of parameter admissible domain. In order to compare to least squares based approach, the MATLAB optimization subroutine FMIN has been used with a precision parameter that is comparable to the signature based results for five different initial conditions, the corresponding number of iterations so obtained was

$$\{68, 14, 52, 43, 76\}_{\text{leastsquares}} \quad \text{vs} \quad \{6\}_{\text{Signature}}$$

which clearly suggests that the signature based approach may be really advantageous since the number of iteration is much lower and independent of the step change or the initial guess value.

VII. Conclusion

In this paper, simulated moving bed diagnosis based on graphical signature tool is proposed. This graphical tool when joined to the particularly powerful human classification ability facilitates the extraction of relevant graphical residuals. The latter can then be expressed in a mathematical form for use in a real time context. Representative numerical results are presented and discussed to demonstrate the performance of the graphical signature tool in diagnosing a set of SMB failures. On line parameters estimation are presented.

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