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DEVELOPMENT OF ONLINE DATA FILTERING BASED ON KALMAN FILTER

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Abstract: Knowledge of accurate process measurements in the form of Flow, temperature and pressure strongly affect product quality, process real time optimization and control, plant safety and plant profitability. The paper reports an experience with online data filtering in Naphtha Hydrotreater setup. First, pilot plant data is analyzed for detecting and removing faulty data and gross errors. To remove noise hidden in the process data, a fast and adaptive data denoising technique is proposed. The proposed technique is based on the recursive least square to identify the pilot plant model and the Kalman filter to reconcile noisy data. This technique offers competitive advantages over conventional approaches: Independent and adaptive model and less computation time. From several pilot runs, the proposed technique has shown good performance in terms of accuracy and speed.

Keywords: *Data Filtering; Kalman Filter; Online; Process Control; Experimental Setup.*

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INTRODUCTION

On-line data filtering is typically used to improve the accuracy of measured process variables and unmeasured variable estimates in monitoring, on-line process optimization and process control. It's widely used in industrial and utility plants [1-4].

The problem of estimating the variables involved in a chemical process, subject to linear balance equations, has been considered by several authors [5-9]. Basic issues are whether the estimation of an observed value can be improved by using the other measurements (redundancy), an unobserved value is estimable from the observed ones (observability) and whether an observed value is a gross error. There are many research works concerning data filtering and reconciliation in recent years [10-15].

Data reconciliation is an optimization method used to filter random errors from measured variables. Also this method can be used to estimate unmeasured variables and model parameters. Prior to data reconciliation, it is necessary to eliminate gross errors from measured variables [16].

In data reconciliation, model equations are constraints of optimization. Based on the type of constraints, data reconciliation can be divided into two ways. According to linearity and nonlinearity of model equations, data reconciliation methods can be categorized in linear and nonlinear ways. Furthermore, based on applying time variable in model equations, data reconciliation techniques can be divided into dynamic and steady state categories [13].

In this paper, an adaptive method for data filtering was applied to an experimental setup of Naphtha Hydrotreater. The results showed a fast and stable convergence of the model parameters. The advantage of this method over other data reconciliation methods is independency of the model to the process. This method estimates its own model. Thus, unlike other methods, it is independent of the process and can be applied on any process. This technique only needs noisy values of input and output variables of the process.

EXPERIMENTAL

The experiments were performed in a pilot plant that was designed and assembled to perform hydro-treating experiments at high pressure. The reactor of this pilot plant is a 400 cm^3 vessel which can operate at pressure less that 55 bar. Figure 1 demonstrates the schematic process flow diagram (PFD) of this pilot. As it is shown in this figure, the feed and hydrogen are mixed with a certain ratio before flowing into the reactor. The mixed feed enters to the reactor with definite pressure to achieve a predetermined temperature for performing the hydro-treating reactions.

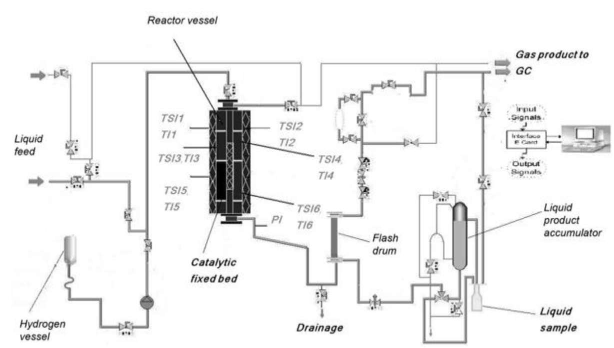

Figure 1: Schematic Process Flow Diagram of Hydro-treating Pilot Plant

There are twelve thermocouples along the reactor for determining the skin and the inside reactor temperature. Six thermocouples are specified to determine the skin temperature and the others are for inside reactor temperature (In Figure 1, TSI's refer to skin temperature indicator and TI's refer to inside reactor temperature indicator). A quarter of the total reactor volume (100 cm3) which is located in the middle of reactor vessel is specified for catalytic fixed bed. This is normally operated at isothermal conditions. The reactor product stream is fed to a flash drum to separate gas and liquid products. The liquid product is accumulated in a drum and the gas product is transferred for online analysis to determine the H_2S and H_2 content of stream.

METHODOLOGY

Formulation Problem of Data Filtering

Data filtering methods are employed to improve accuracy of measured variables. What is meant by accuracy of a variable is the absolute difference between actual and measured value of variable. As affirmed above, data reconciliation is an optimization method with objective function and constraint equations shown as follows:

Objective Function:

$$\mathrm{Min}(\Gamma-\Psi)^{T}\Sigma^{-1}(\Gamma-\Psi) \tag{1}$$

$$\text{Constraints:} \mathrm{F}(\Psi,\mathrm{t}) = 0 \tag{2}$$

Optimization is done using Ψ variables.

Adaptive Data Filtering

Properties of Adaptive Model

The model utilized in two parts of data filtering methods must be as general as possible to be capable of supporting as likely processes. The suggested model includes the following properties: black box, dynamic, linear, discrete, state space, and multiple inputs & outputs. Model equations are as follows:

$$X(k) = AX(k-1) + BU(k-1) \tag{3}$$

$$Y(k) = IX(k) \tag{4}$$

$$A = \begin{bmatrix} -a_{11} & \cdots & -a_{n1} \\ \vdots & \ddots & \vdots \\ -a_{1n} & \cdots & -a_{nn} \end{bmatrix} \tag{5}$$

$$B = \begin{bmatrix} b_{11} & \cdots & b_{m1} \\ \vdots & \ddots & \vdots \\ b_{1n} & \cdots & b_{mn} \end{bmatrix} \tag{6}$$

$$X(k) = \begin{bmatrix} x_1(k) \\ \vdots \\ x_n(k) \end{bmatrix} \tag{7}$$

$$U(k) = \begin{bmatrix} u_1(k) \\ \vdots \\ u_m(k) \end{bmatrix} \tag{8}$$

$$Y(k) = \begin{bmatrix} y_1(k) \\ \vdots \\ y_n(k) \end{bmatrix} \tag{9}$$

Online Identification of Model Parameters

There are various methods to recognize model parameters. In this work, recursive least square identifier is used. This method has an appropriate speed convergence and keeps stability in different situations. In this method using input and output variables of the process on latter sampling time, an estimation of model parameters is provided corresponding to the process on current sampling time. In other words, matrices A and B are determined [14]. The identifier equations are as follows:

$$\hat{\theta}_i^T = [a_{1i} \quad \cdots \quad a_{ni} \; b_{1i} \cdots b_{mi}] \;\; i = 1,2,\dots,n \tag{10}$$

$$\hat{\theta} = [\hat{\theta}_1 \; \hat{\theta}_2 \quad \cdots \quad \hat{\theta}_n] \tag{11}$$

$$\varphi^T(k) = [-y_1(k-1) \quad \cdots \quad -y_n(k-1) \; u_1(k-1) \cdots u_m(k-1)] \tag{12}$$

$$Output^T(k) = [y_1(k) \; y_2(k) \quad \cdots \quad y_n(k)] \tag{13}$$

$$\hat{\theta}(k) = \hat{\theta}(k-1) + \frac{P(k-1)\varphi(k)[Output\ (k) - \hat{\theta}^T(k-1)\varphi(k)]^T}{Alpha + \varphi^T(k)P(k-1)\varphi(k)} \tag{14}$$

$$P(k) = P(k-1) - \frac{P(k-1)\varphi(k)\varphi^T(k)P(k-1)}{Alpha + \varphi^T(k)P(k-1)\varphi(k)} \tag{15}$$

The equations (14) and (15) are solved iteratively.

Estimation of State and Output Variables

Kalman filter is applied to estimate state variables. Kalman filter offers an estimation of noise free state variables using identified parameters of adaptive model and noisy values of input and outputs process variables and also taking variance covariance matrix as a parameter which is a measure of magnitude and distribution of random errors in process variables (Auto covariance Least-Squares or ALS technique is used to calculate the covariance of the noise using MATLAB function) then using these errorless values and equation (4) errorless output variables are attained. Kalman filter equations are as follows [15]:

$$N(k) = AM(k-1)A^T + Q \quad (16)$$
$$M(k) = N(k) - N(k)[R + N(k)]^{-1}N(k) \quad (17)$$
$$K_e(k) = N(k)[R + N(k)]^{-1} \quad (18)$$
$$Z(k) = AX(k-1) + BU(k-1) \quad (19)$$
$$X(k) = Z(k) + K_e(k)[Y(k) - Z(k)] \quad (20)$$

Description of Data Acquisition System

The sensors and actuators in the plant are connected to a PLC/S7-500 control unit. The PLC/S7-500 is connected to a personal computer that runs the SCADA (supervisory control and data acquisition) system CitectSCADA. The data reconciliation algorithm has been implemented directly in Simulink of Matlab and the communication with CitectSCADA is done using the LabVIEW software. Both LabVIEW and the data reconciliation algorithm run on the same personal computer, based on an Intel Core 2 Duo T9600 processor at 2.8 GHz. This computer is connected by a PC Adapter USB to the CitectSCADA computer. The PC Adapter USB is compatible with USB V1.1 and satisfies the requirements for "Low-Powered“USB devices [http://www.siemens.de/simatic-tech-doku-portal].

Properties of the PC Adapter USB

The SIMATIC PC Adapter USB connects a PC to the MPI/DP interface of an S7/M7/C7 system via USB. A slot is not required in the PC, which means that the adapter can also be used for non-expandable PCs such as notebooks. The configuration is presented in Figure 2. Figure 3 shows the block diagram of the USB PC adapter.

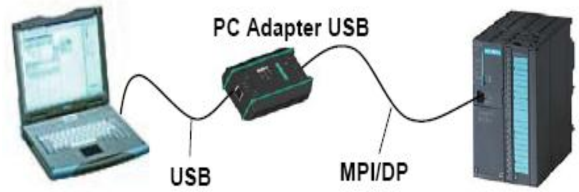

Figure 2: Configuration with PC Adapter USB

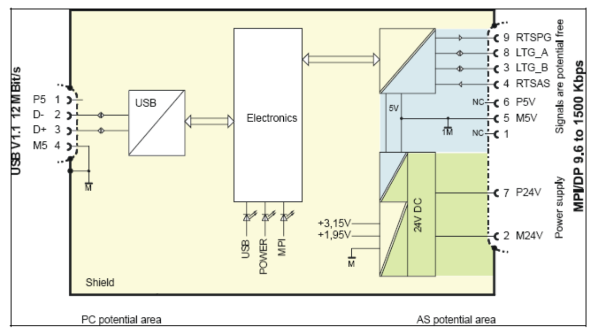

Figure 3: Block Diagram of the USB PC Adapter

LabVIEW Software

LabVIEW software program was used for data acquisition, and instrument control. LabVIEW (Laboratory Virtual Instrumentation Engineering Workbench) is a graphical programming language that has been adopted throughout industry, academia, and government laboratories as the standard for data acquisition and instrument control software [19]. The Matlab software can be used inside of the LabVIEW program and for using Matlab the computer must have a licensed copy of the Matlab software version 6.5 or later installed in the computer because LabVIEW invokes the Matlab software script server to execute a script written in the Matlab language syntax.

RESULTS AND DISCUSSION

The strategy described in section Formulation Problem of Data Filtering has been applied to the Naphtha Hydrotreater setup. First, the pilot plant data is transmitted to workspace of Matlab using the data acquisition system. Then, Simulink gets the data and applies the algorithm to it. In this section, the results will be exposed and discussed.

In Figures 4-8, the graphs of five series of the pilot plant data before and after applying the adaptive data filtering algorithm are presented.

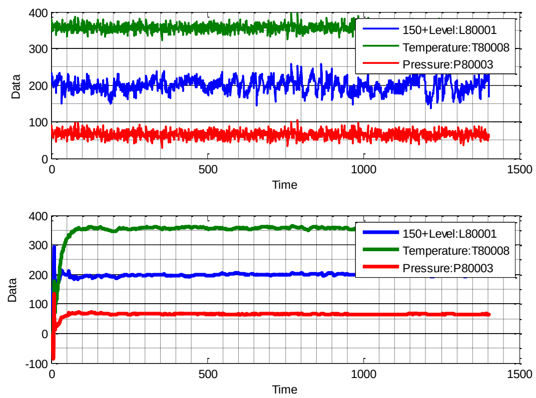

Figure 4: First Series of the Data before and after Filtering

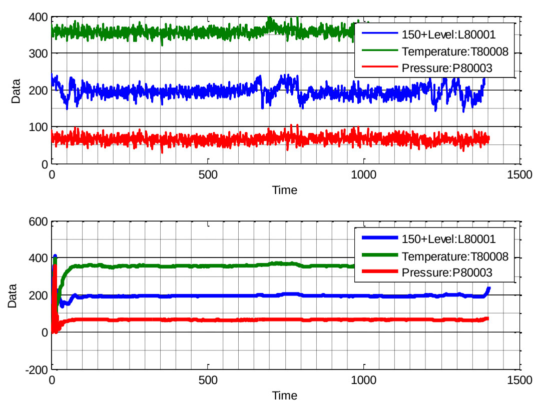

Figure 5: Second Series of the Data before and after Filtering

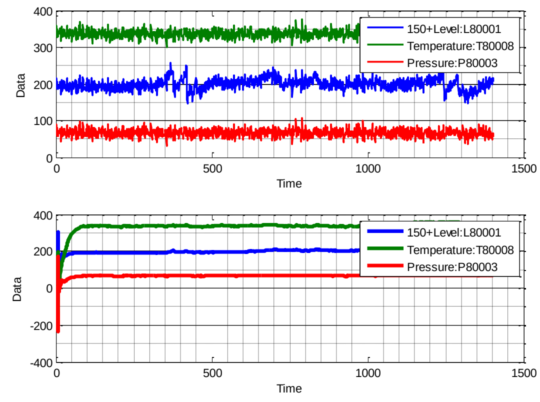

Figure 6: Third Series of the Data before and after Filtering

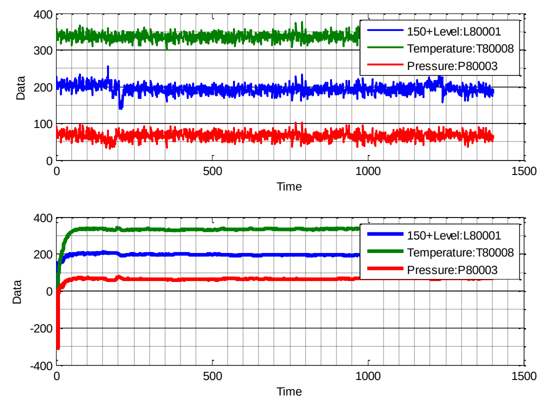

Figure 7: Fourth Series of the Data before and after Filtering

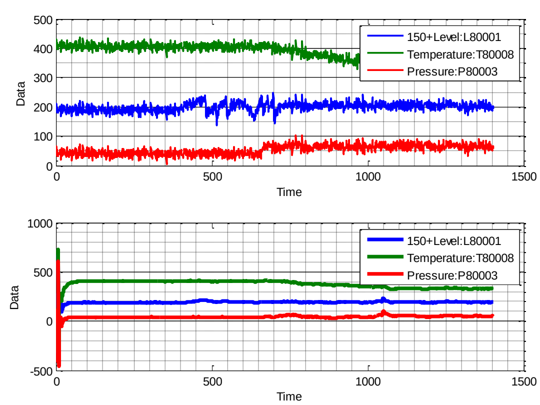

Figure 8: Fifth Series of the Data before and after Filtering

As can be seen, this method filters random errors and noises fast and effectively but there are some deviations at the start of each graph. At the start time, there isn't enough data to tune the model parameters but the adaptation of the parameters gets better over time.

CONCLUSION

In this paper, an adaptive method for data filtering was applied to a Naphtha Hydrotreater setup. The results showed a fast and stable convergence of the model parameters. Certainly, there were some convergence problems at the start time, but the problem was solved over time.

The advantage of the adaptive method over other data filtering methods is independency of the model to the process. This method estimates its own model. Thus, unlike other methods, it is independent of the process and can be applied on any process. From several pilot runs, the proposed technique has shown good performance in terms of accuracy and speed.

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