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APPLICATION OF KALMAN FILTER TO SUPPORT DECISION-MAKING IN THE MAINTENANCE OF HEAT EXCHANGERS IN SLURRY POLYMERIZATION PROCESSES

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Abstract *Fouling is one of the main problems in the operation of heat exchangers since it reduces the heat transfer efficiency. In industrial practice therefore these equipment have to be periodically removed for cleaning. The availability of fouling monitoring methods supports decision making concerning the periodic cleaning and therefore can reduce operational costs. This paper presents a model to estimate the heat transfer coefficient for the slurry polymerization process based on the Extended Kalman Filter (EKF). Some advantages of this proposed method are that neither special sensors nor steady state operating conditions are needed. Results indicate that the EKF can predict the parameter reasonably well with deviations up to 5% at the end of the campaign. The model allows identifying the fouling of the heat exchangers, one of the main drivers of production costs in industry, therefore avoiding unnecessary shut down for maintenance.*

1. INTRODUCTION

The operation of heat exchangers over time usually produces a phenomenon called fouling, which is the deposit of material from a flowing fluid onto the exchanger surface. The deposited layer has a lower thermal conductivity, damaging the heat transfer capacity and the heat exchangers performance as well. Another undesirable consequence is the reduction of cross-sectional area since it offers more resistance to fluid flow [1]. Heat exchangers, then, have to be periodically cleaned. Al-Haj (2012) concluded that around $40,000 to $50,000 are wasted per heat exchanger per cleaning due fouling [2]. The availability of fouling monitoring methods supports decision making concerning the periodic cleaning and therefore might reduce operational costs.

Measurement techniques [3] as ultrasound or radiography are used for measurement of fouling. Another cheaper alternative is the use of mathematical techniques. Simpler methods based only on a model of the heat exchanger or pressure drop [4] can be replaced by more powerful techniques. Riverol and Napolitano [5] used artificial neural networks to predict the overall heat transfer coefficient in a tubular heat exchanger for beer production. Sabrina et al. [1] and Petermeier et al. [6] demonstrated the capacity of fuzzy logic to observe heat transfer coefficient over time. Another approach is the use of Extended Kalman Filter (EKF), a well known method for state estimation [7], to predict the heat coefficient over time as the work of Shoaib [8]. Jonsson et al. [9] showed the advantages of EKF compared to traditional techniques that require that the system must be in steady state operating conditions. Palsson et al. [10] compared the use of the EKF and ANN for fouling detection in a counterflow heat exchanger and the EKF outperforms.

The slurry polymerization process is widely used in the production of polyolefins. The reaction is highly exothermic and the heat generated by the reaction must be removed in order to control the reactor temperature. As Fig. 1 shows, part of the heat generated is removed by the jacket but the greatest part is removed by recirculating the slurry through three external heat exchangers (P-01, P-02 and P-03). The slurry worsens the fouling phenomenon so that it is more critical in this process than in traditional heat exchangers. The dirty walls not only reduce heat transfer capacity but also increase pressure drop and the heat exchangers efficiency. In industrial practice each heat exchanger is monitored independently based on its pressure drop and on the overall energy balance in order to remove it for periodic cleaning. The objective of this study is to develop a model based on EKF for predicting fouling in the heat exchangers of the slurry polymerization process in order to support the decision about shutting down an equipment for cleaning.

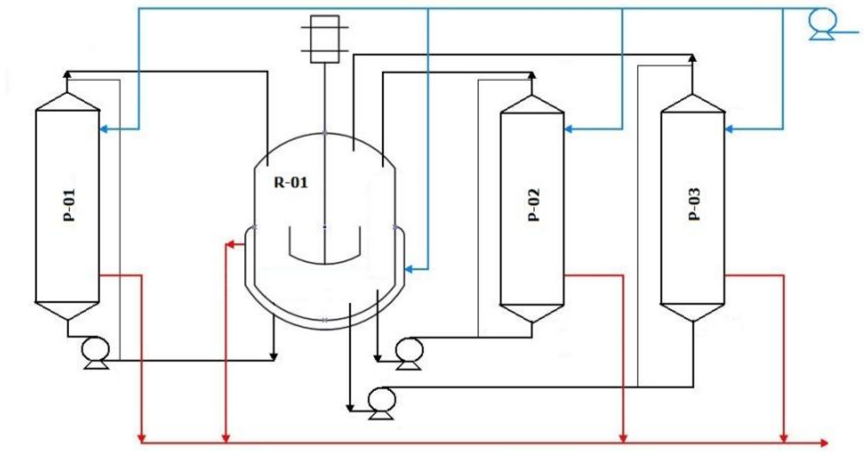

Figure 1. Cooling system of polyethylene manufacturing process

2. PROCESS MODEL

A detailed mathematical model of the polymerization reactor was developed in previous work [11]. The current study focuses on the modeling of the heat exchangers through mass and energy balances. According to Salau [12], who investigated a gas phase polymerization process, the best model to represent a heat exchanger comprises a dynamic model divided into N stages, as Fig. 2 depicts. Therefore, each heat exchanger $k \in [1, 2, 3]$

in Fig. 1 (P_01, P-02 and P-03) is modeled according to:

$$\frac{dT_{w,k,j}}{dt} = \frac{N_k . F_{w,k}}{m_{w,k}} . \left(T_{w,k,j-1} - T_{w,k,j}\right) - \frac{U_k . A_{t,k}}{m_{w,k} Cp_w} \Delta T_{m,k,j} \tag{1}$$

$$\frac{dT_{s,k,j}}{dt} = \frac{N_k . F_{s,k}}{m_{s,k}} . \left(T_{s,k,j+1} - T_{s,k,j}\right) + \frac{U_k . A_{t,k}}{m_{s,k} . Cp_s} \Delta T_{m,k,j} \qquad j = 1, 2, \dots, N \tag{2}$$

where F is the mass flow rate, m is mass in heat exchanger, Cp is specific heat, A_t is the heat exchange area and ΔT_m is the logarithmic mean temperature. The indexes w and s stand for water and slurry respectively. The number of stages (N) that better fits the model has to be investigated. The overall heat transfer coefficient was modeled as a function of time in order to represent the fouling:

$$U_k(t) = U_{k,clean} - (\alpha_k t) \, exp(\beta_k t) \tag{3}$$

where $U_{k,clean}$ is the heat transfer coefficient for the clean heat exchanger $k \in [1, 2{,}3]$. The parameters α and β must be estimated from process data for each equipment. In the real plant the process does not stop due to the maintenance of one heat exchanger, it continues to operate with the other two heat exchangers. Different fouling levels are considered to each heat exchangers increasing from P-01 to P-03.

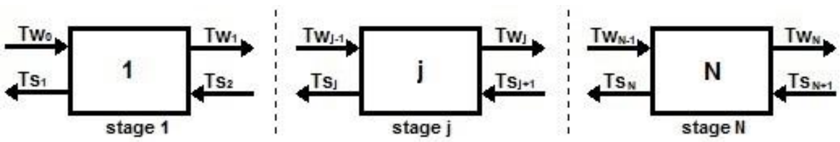

Figure 2. Schematic model of the exchanger with N stages (Adapted from [12])

2.1. Parameter estimation using Extended Kalman Filter

The Extended Kalman Filter (EKF) uses a dynamic and non-linear mathematical model of the process to predict its states. Based on the estimated state and its corresponding measured value, the EKF corrects the prediction minimizing the squared sum of deviations between the predicted and the measured values. The procedure of prediction and correction is repeated at each time instant. The EKF allows estimating the state of a process in the presence of measurement noise, even if the exact model of the process is not known. For more details on EKF, the reader should address to [7].

In order to estimate the heat transfer parameter by the EKF, then, the heat transfer parameter has to be considered as an additional state besides water and slurry outlet temperatures, which are measured. The model representing the heat exchanger $k \in [1, 2{,}3]$ is given as:

$$\frac{dT_{w,k}(t)}{dt} = \frac{F_{w,k}(t)}{m_{w,k}}\left(T_{wi}(t) - T_{w,k}(t)\right) - \frac{U_k(t) A_{t,k}}{m_{w,k} c_{pw}} \frac{(T_{w,k}(t) - T_{si}(t) + T_{wi}(t) - T_{s,k}(t))}{2} + w_w(t) \tag{4a}$$

$$\frac{dT_{s,k}(t)}{dt} = \frac{F_{s,k}(t)}{m_{s,k}}\left(T_{si}(t) - T_{s,k}(t)\right) + \frac{U_k(t)A_{t,k}}{m_s c_{ps}} \frac{\left(T_{w,k}(t) - T_{si}(t) + T_{wi}(t) - T_{s,k}(t)\right)}{2} + w_s(t) \tag{4b}$$

$$\frac{dU_k(t)}{dt} = w_\theta(t) \tag{4c}$$

where F is the mass flow rate, T is the temperature, the subscript i corresponds to inlet stream, m is mass in heat exchanger, Cp is the specific heat, A_t is the heat exchange area and the sub-indexes w, s and θ represent water, slurry and the heat transfer parameter, respectively. A white noise $w(t) \in N(0, Q(t))$, i. e., with zero mean and covariance $Q(t)$ is added to each state. The model representing the heat exchanger in the EKF considers $N = 1$ and the arithmetic mean temperature instead of the logarithm mean temperature. The model might be rewritten using the state space notation, according to:

$$\dot{\mathbf{x}}(t) = \mathbf{A}(t) + \mathbf{w}(t) \tag{5}$$

The measurement model of variable z at time instant i is given by:

$$\mathbf{z}_i = \mathbf{H}\mathbf{x}_i + \mathbf{w}_{z,i}, \quad i = 1, 2, \ldots \quad \mathbf{w}_{z,i} = N(0, R_{z,k}) \tag{6}$$

where $\mathbf{w}_{z,i}$ is the measurement noise, which is Gaussian with zero mean and covariance $R_{z,i}$. It is assumed that the states and measurement noises are uncorrelated, i.e., $E\langle \mathbf{w}(t)\mathbf{w}_{z,i}{}^T\rangle = 0$ for all i and t and $\mathbf{Q}$ and $\mathbf{R}$ represent confidence in the model and the measurements respectively. The matrix $\mathbf{H}$ is the measurement matrix with constants elements, $\mathbf{H} = [1 \quad 0 \quad 0;\ 0 \quad 1 \quad 0]$, since water and slurry outlet temperature are the measured variables.

The extended Kalman filter comprises the following steps, repeated at each time instant:

1. Prediction of states ($\hat{\mathbf{x}}_i$) and error covariance matrix ($\mathbf{P}_i$):

$$\hat{\mathbf{x}}_i(-) = \hat{\mathbf{x}}_{i-1}(+) + \int_{t_{i-1}}^{t_i} \mathbf{A}(t)\, dt \tag{7}$$

$$\mathbf{P}_i(-) = \mathbf{P}_{i-1}(+) + \int_{t_{i-1}}^{t_i} [\mathbf{F}(t)\mathbf{P}(t) + \mathbf{P}(t)\mathbf{F}(t)^T + \mathbf{Q}(t)]\, dt \tag{8}$$

   where the minus sign indicates the prediction step and the plus sign indicates the correction step, $\mathbf{F}(t)$ is the Jacobian matrix applied to the estimated states at the previous moment and is described by:

$$\mathbf{F}(t) = \left.\frac{\partial \mathbf{A}(t)}{\partial \mathbf{x}(t)}\right|_{\mathbf{x}(t)=\hat{\mathbf{x}}(t)} \tag{9}$$

2. .Computation of the Kalman gain:

$$\mathbf{K}_i = \mathbf{P}_i(-)\mathbf{H}^T\left[\mathbf{H}\mathbf{P}_i(-)\mathbf{H}^T + \mathbf{R}_{z,i}\right]^{-1} \tag{10}$$

3. Correction of the estimated states based on the Kalman gain and on the error covariance matrix:

$$\mathbf{P}_i(+) = (\mathbf{I} - \mathbf{K}_i\mathbf{H})\mathbf{P}_i(-) \tag{10}$$

$$\hat{\mathbf{x}}_i(+) = \hat{\mathbf{x}}_i(-) + \mathbf{K}_i[\mathbf{z}_i - \mathbf{H}\hat{\mathbf{x}}_i(-)] \tag{11}$$

3. RESULTS AND DISCUSSION

Initially the number of stages N, representing the heat exchanger discretization, on the model prediction is investigated. Then, the robustness of the Kalman filter with respect to the initial conditions is evaluated and the results of the estimation of the heat exchange coefficient are presented.

3.1. Number of stages of the heat exchanger

The test was performed with sequential step changes in the slurry flow rate (-22%) at $t = 2000$ s and water flow rate (-16%) at $t = 5000$ s for $N = 1,2,3,4$. Figure 3 shows the results for the slurry outlet temperature in the last stage. As can be seen, the number of stages did not show a significant change in the prediction, especially at the stationary condition: the highest deviation in temperature when $N = 2$ compared to $N = 4$ is 0.25 K. As the increment of each stage increases two differential equations, a number of two stages is considered in order to avoid unnecessary increase in the computational effort.

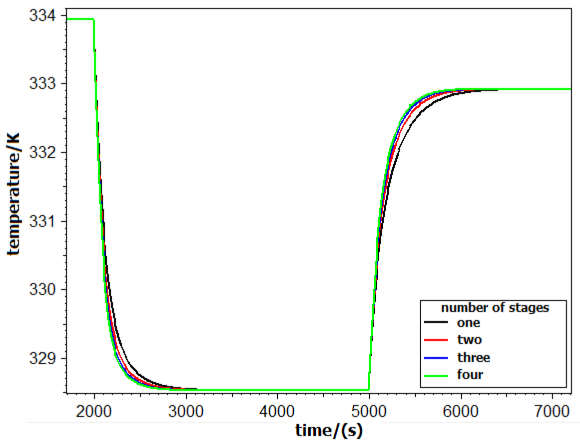

Fig 3 – Evaluation of the number of stages of the heat exchanger model.

3.2 Starting conditions and parameters for the Extended Kalman Filter

According to Paim [13], $\mathbf{P}(0)$ values of the order of 10^2 a 10^3 were assumed in order to ensure fast convergence at the beginning of the estimation. The matrix $R_{z,k}$, which gives the confidence on the measurements, was chosen according to the common values used in literature [9]. In order to determine the matrix $\mathbf{Q}$, diagonal values in the range from 10^{-5} to 10 were investigated. The larger the $\mathbf{Q}$ value, the higher the convergence speed and the higher is the estimation noise. The value of 10^{-3} was chosen as the best speed-to-noise ratio. In order to determine the influence of the initial condition of the heat transfer coefficient on the EKF results, fifty random values with mean 813.6 W/m^2K and standard deviation equals to 50 W/m^2K were tried. Fig. 4 illustrates the estimated parameter of the P-01 exchanger, indicating the robustness of the EKF since, regardless of the initial condition, the convergence is reached. Therefore, parameter values and starting conditions applied to the Kalman Filter are:

$$\mathbf{Q} = \begin{bmatrix} 10^{-3} & 0 & 0 \\ 0 & 10^{-3} & 0 \\ 0 & 0 & 10^{-3} \end{bmatrix} \quad \mathbf{R}_k = \begin{bmatrix} 0.1 & 0 \\ 0 & 0.1 \end{bmatrix} \quad \hat{\mathbf{x}}(0) = \begin{bmatrix} 300.0\ K \\ 356.5\ K \\ 813.6\ W/m^2K \end{bmatrix} \quad \mathbf{P}(0) = \begin{bmatrix} 10^3 & 0 & 0 \\ 0 & 10^3 & 0 \\ 0 & 0 & 10^3 \end{bmatrix}$$

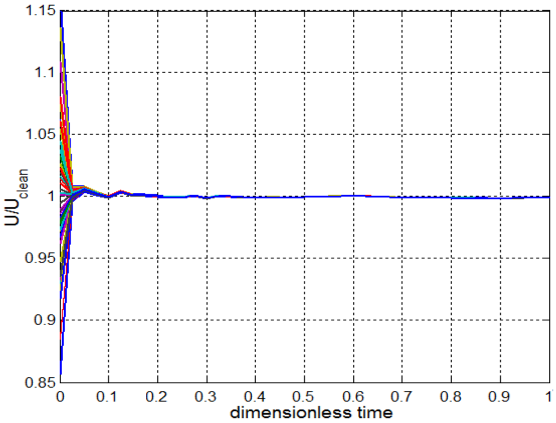

Fig 4 – Comparison of the initial condition of the estimated parameter on the EKF prediction.

3.3 Results for the overall heat transfer coefficients estimation

Fig. 5 shows the water and outlet temperatures as well as the estimated heat transfer coefficient for each heat exchanger when a noise of ± 2% is added to the measurements. EKF acts as a filter for the measured temperatures while estimating the parameter $U(t)$. As fouling increases, i.e. $U(t)$ decreases, $T_w(t)$ decreases and $T_s(t)$ increases due to the lower thermal exchange between the sides of the heat exchanger.

As the rate of fouling increases, estimation becomes more difficult. Fig. 5d shows that, at the end of the operation for the exchanger P-03, the EKF decreases its tracking capacity of the overall heat transfer coefficient. The error, though, reaches a maximum of 5% taking into account the operating time used, therefore a satisfactory prediction is obtained. Best results in the state estimation can be obtained using a smaller sampling rate, despite the increase in the computational effort. Based on these results, the engineers and operators at industrial practice can conclude if the decrease in heat exchanger efficiency is due to fouling, deciding whether to shut down the equipment for cleaning. The availability of the developed model can therefore avoid unnecessary maintenance, reducing operational costs.

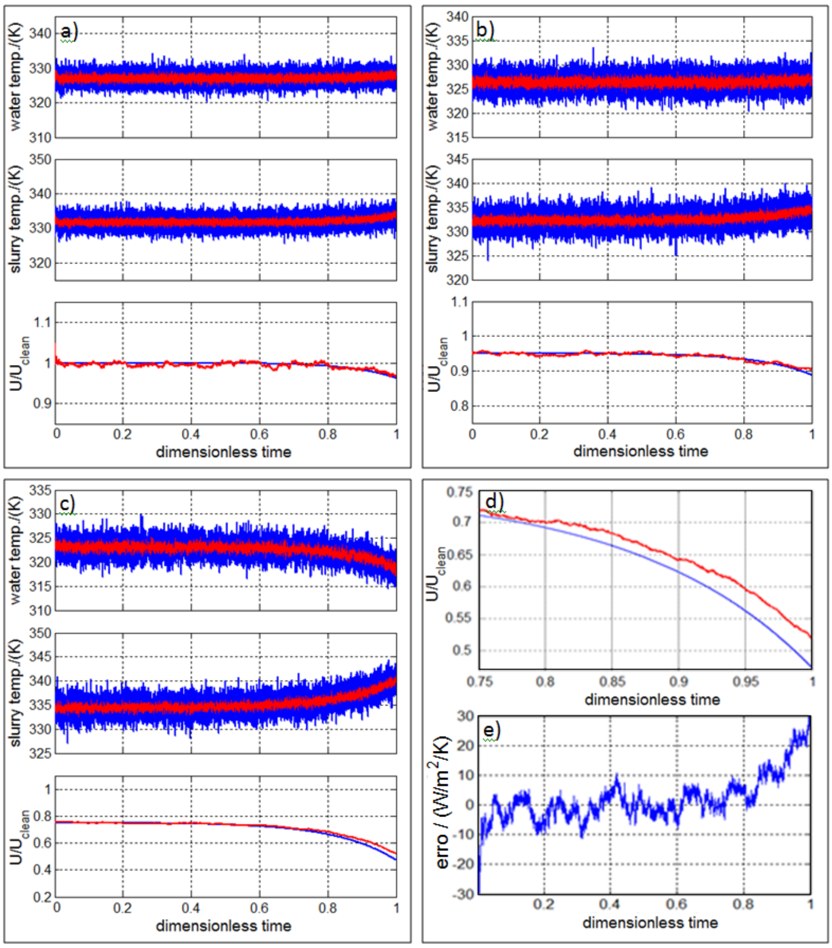

Fig 5 – Results for state estimation. ▬ Process values (simulation). ▬ EKF estimation. a) Heat Exchanger P-01. b) Heat Exchanger P-02. c) Heat Exchanger P-03. d) U/Uclean for Heat Exchanger P-03. e) Error evolution over time for the Heat Exchanger P-03.

4. CONCLUSIONS

Prediction of fouling in heat exchangers is important to help operators and engineers to carry out maintenance at the appropriate time minimizing energy costs and maximizing the productivity. This work seeks to solve the problem of identifying heat exchangers fouling in a slurry polymerization process using the Extended Kalman Filter. Some advantages of this proposed method are that neither special sensors nor steady state operating conditions are needed. Only measurements of the inlet and outlet temperatures in heat exchangers and flows of slurry and water are considered.

The EKF was successfully applied to identify fouling in heat exchangers since the model can predict the heat exchanger parameter with deviations up to 5% at the end of the campaign. The low cost strategy proposed can provide large gains for the industrial plant, supporting the decision-making at operational level and enabling a better schedule for equipment shut down for maintenance.

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