Extended Kalman filter for fouling detection in thermal power plant reheater
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**Abstract**
A model based on-line foul monitoring approach for a power plant reheater is proposed. Dual Extended Kalman Filter (DEKF) is designed to estimate the model parameters that influence fouling. Based on the estimated parameters the performance index (Cleanliness Factor) is obtained to retrieve the extent of fouling on reheater. The simulation and experimental validation using power plant data shows the efficacy of DEKF over conventional Joint-EKF (JEKF) in estimating the model parameters. The outcome of the work will assist in soot blow scheduling for reheater by perceiving the fall in cleanliness factor and will also help in analysing its impact on heat transfer efficiency.

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1. Introduction

In thermal power plants ash fouling is inevitable that degrades the thermal performance of the heat exchanger. It also leads to production loss because of process inability to sustain throughput due to insufficient energy transfer. In order to clean the ash deposit from the heat transfer surface area soot blowers are employed. As it is difficult to estimate ash fouling level, soot blowers in thermal power plants are activated based on conservative schedule which follow a fixed sequence. However, frequent soot blow operation will lead to waste of steam, increased attemperator spray and tube erosion. On the other hand less frequent soot blow operation will lead to decrease in heat transfer efficiency. This motivates the need for criteria based method which activates the soot blowers based on a predefined Cleanliness Factor (CF) that gauges fouling.

Existing fouling detection methods are classified into instrument based methods (direct) and model based methods (indirect). Instrument based methods use sensors for determining the fouling conditions. Only few papers on instrument based methods are reported (Johnson, Subasavage, & Breeding, 2004; Simon, Frach, Jochum, & Lang, 2006); as the practical usage of sensor in harsh condition is limited. In model based approach the output deviation between healthy heat exchanger model and plant data is used for identifying fouling condition. Models developed are either artificial intelligence based models or thermal models that depict either the heat transfer or heat absorption in different sections of heat exchanger. Feed-forward Neural Network (NN) is used to estimate the fouling condition based on locally absorbed heat fluxes (Teruel, Cortes, Diez, & Arauzo, 2005), fouling resistance (Lalot & Palsson, 2010), cleanliness factor and efficiency (Shi & Wang, 2015). Recurrent NN model with optimized network selection is applied to predict fouling in shell and tube heat exchanger (Radhakrishnan et al., 2007). Local linear wavelet NN model developed to predict the temperature difference and efficiency of shell and tube heat exchangers has improved accuracy over conventional neural network (Mohanty & Singru, 2014). Acoustic parameters that are sensitive to changes in heat transfer area are chosen and combined in NN to enhance detection stability (Wallhauber, Hussein, Hussein, Hinrichs, & Becker, 2011). Acoustically measured flue gas temperature is also used to monitor ash fouling in water wall tubes of thermal power plant (Zhang, Shen, An, Niu, & Jiang, 2015). However, acoustic based methods have certain drawback that the measurements are local and so it did not represent the considerable portion of the heat transfer surface. Polynomial fuzzy observer is used in fouling detection at both transient and steady state conditions (Delmotte, Dambrine, Delrot, & Lalot, 2013). Even though they have shown that the estimation time is less than NN (Lalot, Palsson, Jonsson, & Desmet, 2007) and extended Kalman filter (Jonsson, Lalot, Palsson, & Desmet, 2007) based approaches, simulation of fouling by a step change is unrealistic and the estimated parameters are biased. Many authors have proposed thermal model for heat exchangers based on partial differential equations by considering the spatial distribution of temperature (Brahim, Augustin, & Bohnet, 2003; Gao, Sammakia, Murray, Ortega, & Schmidt, 2014), heat transfer coefficient and heat...
flux (Kaptan, Buyruk & Ecder, 2008). Thermal models that carry out real-time calculation of ash fouling in large-sized super heaters of coal fired utility boilers were developed based on thermal resistance (Pena, Ternel, & Dzie, 2013) and distribution of flue gas and steam temperature (Trojan & Taler, 2015). To summarize, the drawback in artificial intelligence based system is that large experimental or real-time data is required to train the models. In thermal models the plant is mimicked by partial differential equations which require numerical solutions involving cumbersome mathematical calculation. Some of the characteristic parameters used in the thermal models are often not available or it is non-measurable due to the absence of monitoring instrument (Li, Zhai, Wang, & Huang, 2016).

In this paper fouling in Reheater (RH) is detected by indirect estimation of CF using Extended Kalman Filter (EKF). The estimation is based on the measured variables, mass flow rates and input/output temperatures of flue gas and steam. Two estimation strategies of EKF, Joint-Extended Kalman Filter (JEKF) and Dual Extended Kalman Filter (DEKF) are applied and their performance are compared. The inference from simulation study is validated using real-time data obtained from thermal power plant.

The organization of the paper is as follows: Section 2 describes the state space model of reheater and overview of JEEKF and DEKF. Section 3 discusses about simulation results and real-time analysis which is followed by the concluding remarks in Section 4.

2. Materials and methods

2.1. Reheater model

The reheater in thermal power plants is used to increase the temperature of the saturated steam that flows from high pressure stage to low pressure stage of a turbine. In general, a reheater is modelled by dividing the heat transfer surface area into n sections in x-direction and s sections in y-direction in both flue gas and steam side. The governing equation of each section in the flue gas and steam side is as follows

\[ \frac{dT_{h,i}(t)}{dt} = \left( 1 - \frac{a_{ij}}{2} \right) T_{h,i-1}(t) + \frac{a_{ij}}{2} T_{h,i}(t) \]

\[ \frac{dT_{c,i}(t)}{dt} = \left( 1 - \frac{\beta_{ij}}{2} \right) T_{c,i-1}(t) - \frac{\beta_{ij}}{2} T_{c,i}(t) \]

where the parameters are given by

\[ a_{ij} = A_{h,i}(t) \frac{m_{h}(t)}{m_{b}(t)} ; \quad r_{h}(t) = A_{h,i}(t) \frac{m_{h}(t)}{m_{e}(t)} \]

\[ \beta_{ij} = A_{c,i}(t) \frac{m_{c}(t)}{m_{e}(t)} ; \quad r_{c}(t) = A_{c,i}(t) \frac{m_{c}(t)}{m_{e}(t)} \]

where, \( A \) is the heat transfer surface area (m²), \( M \) — overall heat transfer coefficient (W/m²K), \( M \) — mass of the fluid, \( m \) — mass flow rate (kg/s) and \( c \) is specific heat (J/kgK). Subscript h and c represent the hot and cold section with i and j indicating the position of a section where i = 1, ..., n and j = 1, ..., s.

Jonsson, Palsson, and Seijling (1992) showed that two sections are sufficient to describe industrial heat exchangers and multiple sections are required only for lengthy heat exchangers where the time delay is long. In this study, the RH model is developed with two sections in both x and y direction (i.e. n = s = 2) as shown in Fig. 1. The arrows indicate the direction of mass flow, \( T_{h,10}, T_{h,20} \) and \( T_{e,01}, T_{e,02} \) are the inlet temperatures of flue gas and steam respectively; and the states \( T_{h,12}, T_{h,22}, T_{c,11}, T_{c,22} \) are assumed to be measured (℃).

The overall heat transfer coefficient is defined by

\[ \frac{1}{UA} = \frac{1}{U_{h}A_{h}} \frac{1}{U_{c}A_{c}} = \frac{1}{h_{h}A_{h}} + \frac{1}{h_{c}A_{c}} + \frac{R_{f}}{A_{h}} \]

(4)

The convective heat transfer coefficient of flue gas and steam is denoted by \( h_{h} \) and \( h_{c} \) (W/m²K) respectively and the fouling factor is denoted by \( R_{f} \) (W/m²K). Empirical relations of the heat transfer coefficients are used to account for mass flow dependency and to have a wide range of operating conditions (Jonsson et al., 1992). Hence the overall heat transfer coefficient for a clean heat exchanger (i.e. \( R_{f} = 0 \)) is given as

\[ U = K \left( \frac{m_{h}(t) \omega_{h}(t)}{m_{c}(t) + n_{c}(t)} \right)^{y} \]

(5)

where \( K \) and \( y \) are constants. Since the flow of flue gas and steam in the RH tubes is turbulent, \( y \) is assumed to be 0.8 (Incropera & DeWitt, 2002). To account for variations in mass flow rates the parameters are scaled to reference flows \( m_{h}^{*} \) and \( m_{c}^{*} \). Thus the model parameters take form as,

\[ a_{ij} = a^{*} \frac{m_{h}^{*} A_{h,i}(t)}{m_{b}(t) U^{*}} \quad ; \quad r_{h}(t) = \frac{c_{h}^{*} m_{h}^{*} A_{h,i}(t)}{m_{e}(t) U^{*}} \quad ; \quad r_{c}(t) = \frac{c_{c}^{*} m_{c}^{*} A_{c,i}(t)}{m_{e}(t) U^{*}} \]

(6)

\[ a^{*}, c_{h}^{*}, c_{c}^{*} \] are obtained from Eq. (3) and \( \frac{1}{U^{*}} = \left( \frac{m_{h}^{*} A_{h,i}(t)}{m_{c}^{*} A_{c,i}(t)} \right)^{\frac{y}{y}} \).

2.2. Extended Kalman filter

CF is a widely used performance parameter to assess fouling and it is defined as the ratio between the fouled and clean heat transfer coefficient, \( U(t) \). It varies between 0 and 1 with the maximum value indicating a clean tube. The clean heat transfer coefficient is obtained by theoretical calculations using Eq. (4). The fouled heat transfer coefficient is indirectly obtained through the parameters \( a(t) \) and \( \beta(t) \). EKF solves the parameter estimation problem by the model described in Eqs. (1) and (2) where the overall heat transfer coefficient is linear with respect to flue gas and steam temperature and nonlinear with respect to flue gas and steam mass flow rate.

The energy balance equation at each section of the aforementioned RH model is given by

\[ \frac{d}{dt}T = A \left( \begin{array}{c} T_{h} \ T_{c} \end{array} \right) T + B \left( \begin{array}{c} m_{h} \ m_{c} \end{array} \right) \]

(7)

where \( m = [m_{h} m_{c}]^{T} \), \( T = [T_{h,10} T_{h,20} T_{c,01} T_{c,02}]^{T} \in \mathbb{R}^{4} \) represents the temperature in each section of flue gas and steam side and the model parameters are contained in \( \Phi \). The detailed formulation of RH model is shown in Appendix A.

Eq. (7) is functionally represented in discrete form as

\[ \bar{T}(k) = F(k-1) \bar{T}(k-1) + G \bar{T}_{w}(k-1) \]

(8)

where \( F(k-1) \) is \( \exp(A_{i}(k-1:d) dt) \) and \( G = B \Delta t; \Delta t \) is the sampling time.

The measurement equation that relates the states with measured variables, flue gas outlet temperature \( (y_{1}) \) and steam outlet temperature \( (y_{2}) \), is defined as

\[ \begin{bmatrix} y_{1} \\ y_{2} \end{bmatrix} = C \bar{T}(k) \]

(9)

with \( C = \begin{bmatrix} 0 & 0.5 & 0 & 0.5 & 0 & 0 & 0 & 0 & 0 & 0 \end{bmatrix}^{T} \).

The EKF compensates for stochastic disturbance in both RH model and measurement equation which is described by

\[ \bar{T}(k) = F(k-1) \bar{T}(k-1) + G \bar{T}_{w}(k-1) + w(k) \]

(10)

\[ y(k) = C \bar{T}(k) + \nu(k) \]

(11)

where \( w(k) \in \mathbb{R}^{3} \) is the process noise and \( \nu(k) \in \mathbb{R}^{3} \) is the measurement noise. The process noise and the measurement noise sequence are assumed to have zero mean with covariance matrices \( Q \) and \( R \) respectively. EKF determines the conditional probability density function of the state \( p(T(k)|y(k)) \), where \( y(k) \) denotes the set of measurements \( \begin{bmatrix} y_{1} & y_{2} \end{bmatrix}^{T} \). The conditional posterior density is estimated in two steps:
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