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Dynamic crude oil fouling prediction in industrial preheaters using optimized ANN based moving window technique

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ABSTRACT

The objective of this paper is to develop and validate a reliable, efficient and robust artificial neural network (ANN) model for online monitoring and prediction of crude oil fouling behavior for industrial shell and tube heat exchangers. To explore the complex dynamics of fouling, a new modeling strategy based on moving-window neural network approach is proposed. The essential character of this modeling approach is online updating of the ANN model whenever a new data block is available, so that it can effectively capture the slowly changing of process dynamics. The results of these models have been compared with appropriate sets of experimental data. The mean relative errors (MRE) of training and prediction subsets were about 6.61% and 8.06%, respectively. Since the data extraction in the refinery was performed every 2 h, the modeling approach led to an MRE of about 8% for fouling rate prediction of the next 50 h.

Keywords: Fouling; Crude oil; Preheat exchanger; Dynamic prediction; Moving window; ANN

1. Introduction

Fouling in preheat exchangers of crude distillation units (CDU) produces significant cost penalties due to reduced energy efficiency, increased pressure drop, maintenance requirements and productivity loss. In each refinery, the incoming crude oil must be heated from ambient to elevated temperature in a network of shell and tube heat exchangers. A simplified schematic of preheat train in a CDU is illustrated in Fig. 1. Generally, crude oil flows through the tube side while various other hot streams, coming out of the atmospheric and vacuum distillation columns, flow through the shell side of preheat exchangers. The crude oil coming from storage tanks is normally fed to the preheat unit at ambient temperature. The crude oil is then heated to around 110–150 °C before entering the desalter unit. Downstream of the desalter, crude oil flows through the rest of preheat train and typically reaches to around 230–300 °C before entering to the furnace.

About half of the financial penalties due to fouling in an oil refinery are attributed to the CDU (Lemke, 1999). The worldwide costs, associated specifically with crude oil fouling in preheat trains were equated to around 20% of all heat exchanger fouling, which is estimated to be of the order of \$4.5 million/year (Müller-Steinhagen, 2000). The cost of fouling has also been estimated to around \$1.3 billion per year for the USA refineries in 1995 (Yeap et al., 2004). It arises from additional fuel required for the furnace, production loss during undesirable shutdowns, online cleaning devices and also environmental penalties. Estimates have been made of fouling costs due primarily to wasted energy through excess fuel burn that are as high as 0.25% of the gross national product (GNP) of the industrialized countries. Many millions of tonnes of carbon emissions are the result of this inefficiency. Costs associated specifically with crude oil fouling in the preheat trains of oil refineries worldwide were estimated in 1995 to be of the order of \$4.5bn per year (HIS website, 2010).

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Nomenclature

A_o	external heat transfer area of tube bundle (m^2)
a	input time lag of pseudo-dynamic structure of neural network
b	output time lag of pseudo-dynamic structure of neural network
C_p	specific heat capacity (J/kg/K)
du	input time lag of neural network model
dy	output time lag of neural network model
E	Parameter in the ESDU equation = 0.0225exp(−0.0225Ln(Pr)^2)
F_T	temperature correction factor
h_i	ideal tube-side heat transfer coefficient
h_{ideal}	ideal shell-side heat transfer coefficient
h_{io}	ideal tube-side heat transfer coefficient based on out-side diameter
h_o	real shell-side heat transfer coefficient
ID	tube inside diameter (m)
J_C	baffle cut correction factor
J_L	baffle leakage correction factor
J_B	bundle bypass correction factor
J_R	laminar flow correction factor
J_S	correction factor for variable baffle spacing
J_μ	viscosity correction factor at wall temperature
m	number of spans that allocated as the validation subsets
$\dot{m}$	crude oil mass flow rate (kg/h)
N	number of data subsets in one training block
N_{max}	selective maximum number of hidden neurons in leave-one-out cross-validation method
Nu	Nusselt number
n	number of hidden neurons
OD	tube out-side diameter (m)
P	number of input patterns in neural network model
Pr	Prandtl number
Q	overall heat load (W/K)
Re	Reynolds number
R_f	fouling resistance (m^2 K/W)
S	number of all data spans (equal to the number of all data divided by span size)
St	Stanton number
T_{in}	tube side input temperature (K)
t_{in}	shell side input temperature (K)
t	time (h)
U_C	clean overall heat transfer coefficient (W/m^2/K)
U_D	dirty overall heat transfer coefficient (W/m^2/K)
u	crude oil inlet velocity (m/s)
$u(t)$	input of neural network model
X	input signal vector in pseudo-dynamic structure of neural network
y_i	measured (desired) output values of neural network
$\hat{y}_i$	values of neural network predicted output
y(t)	output of neural network model
Y	output signal vector in pseudo-dynamic structure of neural network

Greek letter

ρ	density (kg/m^3)
ΔT	temperature difference
ΔT_{lm}	LMTD temperature difference

Subscripts

lm	LMTD
p	counter of P as number of input patterns in neural network model
s	counter of S as number of all data spans

Different fouling mechanisms are likely to occur in different heat exchangers. In the cold-end exchangers (upstream of the desalter), deposition of salts, waxes and corrosion products is common. Downstream of the desalter, however, chemical reaction fouling is the dominant mechanism due to the elevated temperatures of crude oil in these preheaters (Yeap et al., 2004). Accurate modeling and prediction of fouling behavior is, normally, hindered due to the lots of simultaneous mechanisms which are involved in crude oil fouling phenomenon.

Several groups of researchers have investigated different modeling techniques to predict crude oil fouling in preheat exchangers. For several years threshold fouling models have been solely used to predict such a complex phenomenon (Ebert and Panchal, 1995; Jafari Nasr and Majidi Givi, 2006; Panchal et al., 1997; Polley et al., 2002; Yeap et al., 2004). The strongly nonlinear nature of crude oil fouling arising from the simultaneous asphaltene chemical reactions and salt and wax deposition could not be properly predicted by semi-empirical models. In fact, these models have intrinsic limitations due to their much simplification used to predict deposition and removal mechanisms. Artificial neural network (ANN) modeling now provides an alternative approach, which often results in better predictions than the classical threshold fouling models (Aminian and Shahhosseini, 2008, 2009). The literature also contains a number of more recent papers specifically related to ANN modeling of fouling phenomenon in different processes (Lalot and Lecoeuche, 2003; Lalot, 2006a,b; Malayeri and Steinhagen, 2003; Radhakrishnan et al., 2007; Romeo and Gareta, 2006; Teruel et al., 2005).

Fouling deposits are the result of combined chemical reactions and physical changes that occur when crude oil is exposed to high metal surface temperatures in a heat exchanger. Incompatibility between asphaltenes and oil results in precipitation of deposits, which adhere to metal surfaces and subsequently carbonize to infusible coke (Dickakian and Seay, 1998; Wiehe et al., 2001). Afterwards, the thickness of deposited layer increases up to plugging the whole tube cross sectional area. These entire phenomena imply that crude oil fouling is a time-dependent process and must be modeled via a dynamic approach.

Recurrent neural networks (RNNs) are capable of representing arbitrary nonlinear dynamical mappings, such as those commonly found in nonlinear time series prediction. RNNs have been reported as a useful feed-forward back-propagation neural network for modeling of time-dependent processes (Haykin, 1999; Himmelblau, 2008). According to Eq. (1), neural network models are commonly used to estimate only the next value of a time series:

$$y(t+1) = f[y(t), \ldots, y(t-dy+1); u(t), \ldots, u(t-du+1)], \qquad (1)$$

where $u(t)$ and $y(t)$ denote the input and the output of the model at current sampling time, respectively. The parameters $du > 1$ and $dy > 1$, with $du < dy$, are the appropriate time