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Fouling analysis of a shell and tube heat exchanger using local linear wavelet neural network

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ABSTRACT

A local linear wavelet neural network based model has been developed to predict the temperature differences on both the tube and shell side and the heat exchanger efficiency. This network replaces the straightforward weight by a local linear model. The working process of the proposed network can be viewed as to decompose the complex, nonlinear system into a set of locally active submodels and then smoothly integrate those submodels by their associated wavelet basis functions. For a given approximation or prediction problem with sufficient accuracy, the local linear models provide more power than a constant weight model as the dilation and translation parameters of LLWNN are randomly generated and optimized without predetermination. The closeness of the predicted results with the actual experimental results and higher accuracy with maximum error of 1.25% indicates that LLWNN can be used as a suitable tool for simulation of heat exchangers subjected to fouling.

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1. Introduction

The accumulation of unwanted deposits on the heat transfer surfaces of a heat exchanger is usually referred to as fouling. Fouling is a major unresolved problem in heat exchangers since their invention. The serious financial and performance consequences of these problems have raised the profile of heat exchanger fouling as an important area of study. 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 [1].

Several studies have been conducted in this regard and many techniques have been developed to evaluate and reduce fouling. Ebert and Panchal [2] first introduced the theoretical concepts to the phenomenon of fouling. They modeled the fouling process using a rate equation and introduced the concept of threshold temperature below which fouling is minimum. Threshold models for crude oil fouling developed by Polley et al. [3] presented a logical framework for analyzing chronic fouling problems in refinery pre-heat trains. The model incorporated simple modifications to the Ebert and Panchal model by considering wall temperature instead of film temperature in the reaction term and retained the dependency of velocity in form of Reynolds number in the generation term. Saleh et al. [4] studied the effect of fluid properties and operating conditions, with the intention of using the results to guide a fouling mitigation strategy. The observations of fouling rates showed a relatively strong effect of surface temperature, bulk temperature, a small effect of pressure and a decrease in fouling rate with increase in velocity. Coletti and Macchietto [5] developed a dynamic mathematical model capable of describing tube-side crude oil fouling in shell-and-tube heat exchangers as a function of local conditions throughout the unit. This model was able to devise a procedure to systematically analyze plant data and estimate necessary model parameters using primary plant measurements such as temperatures and flow rates rather than derived fouling resistances. Several approaches have been presented for the estimation and prediction of fouling behavior in a heat exchanger. These include tabulated time-independent fouling resistances such as TEMA tables, rules of thumb that approximate 25% overdesign, bench scale measurements under accelerated conditions, empirical or semi-theoretical correlations based on laboratory experiments and numerical simulations such as CFD.

However all these methods have significant limitations in accurate prediction of fouling behavior of a heat exchanger. The application of the TEMA fouling resistances does not consider any effects of operating conditions such as flow velocity, temperature, foulant concentration or flow geometry such as baffles, corrugations on the extent of fouling [6]. Similar conclusions may be drawn for proportional overdesign. Empirical models based on laboratory or pilot plant measurements may be useful as long as the

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Nomenclature

A^e	the experimental output data
A_j	dilation parameter
A^p	the predicted output of ANN
ANN	artificial neural network
B_j	translation parameter
CF	cleanliness factor
CDC	correct directional change
K	the number of free model parameters
LPH	liter per hour
LLWNN	local linear wavelet neural network
m	number of mother wavelet nodes
N	the number of observations
R^2	coefficient of determination
R	the fouling resistance (m^2 K/W)
t_i	tube inlet temperature (°C)
T_i	shell inlet temperature (°C)
U	overall heat transfer coefficient (W/m^2 K)
U_c	overall heat transfer coefficient under clean condition
U_f	overall heat transfer coefficient under fouled condition
V	volume flow rate (LPH)
w	weight connecting the hidden layer unit to the output layer unit
WNN	wavelet neural network
ΔT	temperature difference (°C)
ΔP	pressure drop on tube side (kPa)
η	efficiency of heat exchanger in terms of Cleanliness factor
φ	wavelet activation function
Ψ	mother wavelet function

actual fouling process is not significantly different in any major aspect. But extrapolations to different conditions or general predictions are not possible as the physical phenomena underlying fouling are extremely complex. Regression models may be partially theory-based or completely empirical. In both cases, it is not known a priori how many explanatory variables and parameters have to be included in the model for obtaining an optimal regression model. All of these shortcomings led to the development of a model based on artificial neural network, which can effectively predict nonlinear behavior of a heat exchanger with limited experimental data [7].

The ANN analysis as a new paradigm represents an excellent candidate for the purpose of solving thermal problems which involve a multitude of fundamental disciplines, their interactions and complex geometry [8]. The ANN analysis deals with time-dependant dynamic thermal phenomena of heat exchangers more accurately than traditional correlated models. This is certainly a benefit for modeling phenomena such as fouling in which the interaction of the dominant variables is not firmly established [9]. Artificial neural network (ANN) being an important class of empirical technique to model nonlinear, complex or little understood processes with large input–output data sets, the heat transfer performance analysis of heat exchangers has been successfully utilized by many researchers. Radhakrishnan et al.[10] developed a predictive model using statistical methods which can predict the rate of the fouling and the decrease in heat transfer efficiency in a heat exchanger. Malayeri and Müller-Steinhagen [11] investigated the formation of fouling deposits on heat transfer surfaces by highlighting governing fouling mechanisms and introduced a revolutionary prediction method using radial basis functions. Wang et al. [12] applied artificial neural network for heat transfer analysis of shell-and-tube heat exchangers with segmental baffles or continuous helical baffles.

Time-series forecasting is an important area of research and application in thermal systems. Much effort has been devoted over the past several decades to the development and improvement of time series forecasting models. Wavelet neural networks (WNNs) have been introduced as an alternative to MLPs that overcome their shortcomings [13]. WNN models combine the strengths of discrete wavelet transform and neural network processing to achieve strong nonlinear approximation ability, and thus have been successfully applied to forecasting and function approximations. Xie and Zhang [14] developed two WNN models based on different mother wavelets and used for short-term traffic volume forecasting. Mellit et al. [15] used adaptive wavelet-network architecture in finding a suitable forecasting model for predicting the daily total solar-radiation. The performance of the model was compared with different neural network structures and classical models and the results indicated that the model predicted daily total solar-radiation values with a good accuracy of approximately 97% and the mean absolute percentage error was less than 6%. Postalcioglu and Becerikli [16] presented a nonlinear system and function learning by using wavelet network and concluded that raining algorithms of wavelet networks required a smaller number of iterations when compared with neural networks. Based on a complete practical guide provided by Alexandridis and Zapranis [17], wavelet networks are a new class of networks which have been used with great success in a wide range of applications. Due to the advantages of WNNs as universal approximators, the fact that they have more compact topology than other neural networks and their fast learning speed owing to the constitution of the localized wavelet activation function in the hidden layer, WNNs had received much attention from other researchers and have been used extensively to solve numerous real world problems such as face recognition, time-series prediction, pattern classification and system identification [18].

The objective of this paper is to develop a methodology based on local linear wavelet neural network approach for prediction of fouling behavior in a shell and tube heat exchanger, which considers various performance parameters such as temperature differences in each side and the exchanger efficiency. In this work, the efficiency of the exchanger is defined in terms of cleanliness factor (CF) which is a heat transfer performance indicative parameter of a heat exchanger. Moreover, this work predicts the behavior of a heat exchanger subjected to fouling so that an optimal cleaning schedule can be developed without hindering the operation of a plant involving the heat exchanger.

2. Neural network analysis

The artificial neural network technique offers an alternative approach to the problem of information compression for heat exchangers. It is a procedure that is usually used for predicting the response of a physical system that cannot be easily modeled mathematically. The network is first trained by experimentally obtained input–output sets of data, after which it can be used for further prediction. Once a network is trained using the experimental data; the constants or parameters of the trained network can then be transferred further to calculate the

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