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Prediction of asphaltene precipitation in crude oil

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ABSTRACT

Asphaltene are problematic substances for heavy-oil upgrading processes. Deposition of complex and heavy organic compounds, which exist in petroleum crude oil, can cause a lot of problems. In this work an Artificial Neural Networks (ANN) approach for estimation of asphaltene precipitation has been proposed. Among this training the back-propagation learning algorithm with different training methods were used. The most suitable algorithm with appropriate number of neurons in the hidden layer which provides the minimum error is found to be the Levenberg–Marquardt (LM) algorithm. ANN's results showed the best estimation performance for the prediction of the asphaltene precipitation. The required data were collected and after pre-treating was used for training of ANN. The performance of the best obtained network was checked by its generalization ability in predicting 1/3 of the unseen data. Excellent predictions with maximum Mean Square Error (MSE) of 0.2787 were observed. The results show ANN capability to predict the measured data. ANN model performance is also compared with the Flory–Huggins and the modified Flory–Huggins thermo dynamical models. The comparison confirms the superiority of the ANN model.

1. Introduction

Complex and heavy organic compounds, which are called asphaltene, cause many problems in crude oil production, and residual processing. Deposition of asphaltene, in crude oil, can make a number of problems. Solid precipitation around the separators, pumps, tanks and other equipment especially the well pipe in many conditions may threaten the economic oil recovery or considerably increase production costs. Different side effects for asphaltene deposition have been known such as: (CO2, rich gas), ph shift, mixing of crude oil streams, incompatible organic chemicals, stimulation, pressure drop, streaming potential charge and bare metal surfaces (Hirschberg et al., 1984; Pazuki and Nikookar, 2006; Fazlali et al., 2006, 2007). In order to predict the asphaltene precipitation an exact model is necessary to predict the amount and the conditions of precipitation (Hirschberg et al., 1984; Fazlali, 1999; Fazlali et al., 2006; Pazuki and Nikookar, 2006; Fazlali et al., 2007; Söze et al., 2004a,b).

The acceptation of a method approach, obtained exclusively from the experimental data, can provide other practical methods for modeling. These models provide a dynamic relationship between input and output variables and bypass underlying complexity inside the system. Statistical models based on regression analysis are an example of such black box modeling. Most of these common approaches rely on linear system identification models. The major processes found in chemical engineering are unfortunately nonlinear processes, and previously mentioned approaches fail to respond correctly because of process nonlinearity. Recently, another promising alternative modeling technique, ANN, has undergone numerous applications in chemical engineering (Zahedi et al., 2005a,b; Zahedi et al., 2006; Vallés, 2006). It should be mentioned that neural networks had been widely applied on different technology disciplines with successful results. The ability to learn the behavior of the data generated by a system gives neural networks its versatility (Vallés, 2006). In the remaining part of current study after brief description of ANN, experimental routines will be presented. In another part attempts to build the best ANN predictor will be described. Finally the results of ANN will be compared with two common thermodynamical models.

2. Artificial neural network (ANN)

In order to find a relationship between the input and output data driven from accelerated experimentations, a powerful method than traditional modeling is necessary. ANN is an especially efficient algorithm to approximate any function with finite number of discontinuities by learning the relationships between the input and the output vectors (Vallés, 2006; Hagan et al., 1996). Thus, ANN techniques are especially useful for modeling highly nonlinear systems very well. Artificial neural networks are a biological inspiration based on various characteristics of the brain functionality. Artificial neurons are simple computational devices that are highly

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interconnected and the connections between neurons determine the transfer function of the network. An artificial neural network determines an empirical relationship between the inputs and the outputs of a given system. Where the inputs of the system are the independent variables and the outputs are the dependent variables. Therefore, it is important for the user to have a good understanding of the science behind the underlying system to provide the appropriate input and, consequently, to support the identified relationship. A network is composed of units or nodes, which represent the neuron body. The units are interconnected by links that act like axons and dendrites of their biological counterparts. A typical interconnected neural network is shown in Fig. 1. (Zahedi et al., 2005a,b, 2006; Vallés, 2006).

In the above figure an input layer, a central or hidden layer and an output layer can be seen. In a network each connecting line has an associated weight. Two important abilities of the neural network (NN) are supplying fast answers to a problem and the capability of generalizing answers, providing acceptable results for unknown samples. In this way, they should learn about the problem under study and this learning is commonly named training process. Training usually begins with random value for the weight of NN. Then, NNs are supplied with a set of samples belonging to a problem domain to modify the values of their weights. There are various learning algorithms to train neural networks. Some of the famous algorithms are: Perceptron, Hebbian, Widrow–Hoff, and Back propagation. The latter is a suitable algorithm for this research because it has the capability of training multilayer neural networks for function approximation. The key idea of the variable learning rate is to modify the weights and biases update by changing the momentum and the learning rate, based on the behavior of the squared errors. One of the well-known topologies of neural networks for learning is the Multi-Layer Perceptron (MLP), which is used for the classification and the estimation problems (Zahedi et al., 2005a,b; 2006). An MLP is an NN with three layers, an input layer, a hidden layer and an output layer. The input layer represents the incoming pattern and the output layer is the output of the network. Each layer consists of a series of nodes, interconnected with weights. During the learning cycle, the MLP is presented with an input pattern on the input nodes and a target pattern on the output layer. The weights are then updated so that the network gives the desired output. Each node contains an activation function, which is a function that decides whether the neuron should fire depending on its inputs. After training (when the network is put to use), the values of the weights and the activation functions decide which nodes fire. These activation functions come in many different forms, the classics being threshold, sigmoid Gaussian and etc. (Lang, 2006). For more details of the various activation functions see Bulsari (Bulsari, 1995).

3. Experimental data

3.1. Materials and methods

To build an ANN for predicting the asphaltene precipitation, the experimentation in the lab was done (Fig. 2). In selecting the data for modeling, and to ensure that they represent normal operating ranges, off data were deleted from the data list. The data which are not in the normal trend of the process and are not rational are considered as off data and are deleted. The data sets were collected from the six samples of crude oils. Two data sets of collection were made ready from Buenrostro-Gonzalez et al. (2004) Rassmdana et al. (1996) which they reported the experimental data of the asphaltene precipitation and the other data sets (4 sets) were prepared from the different reservoirs of Iranian crude oil from the EOR research center of the NIOC laboratory (Fazlali, 1999). At this experimental section for the recognition of components, the separation of crude oil into two portions (light and heavy) was done by a simple distillation at first step. Then the light section was analyzed by gas chromatography for concentration analysis and determining the average molecular weight. Also the average molecular weight of heavy part was determined by the freezing point method. All of these equipments were prepared based on the IP-86 standard. At the second step, calculating the amount of asphaltene deposition was performed based on the IP standard. In fact, the amount of asphaltene precipitation in oil samples have been calculated by adding *n*-C5, *n*-C6, *n*-C7, *n*-C9 and *n*-C12 precipitants in different proportions of solvent volume ratio. The specified amount of precipitant as *n*-C5, *n*-C6, *n*-C7, *n*-C9 or *n*-C12 was used for an obvious crude oil. The vessels of samples were shacked during these experiments by a shaker. After 2 h, by using a paper filter (Wattman-No. 42) the formed precipitate was separated from the mixture and the weighted. This residue is named asphalt. After that, the asphalt was boiled for 30 min and filtered again. The precipitation is solved in toluene and filtered in another time, the remaining is pure asphaltene solution that must be dried in the oven. All of the experiments were performed based on the IP-143 standard method. As shown in Figs. 5 and 6, the mass fraction of asphaltene with the solvent ratio was studied. At a high solvent ratio the high asphaltene's mass fraction is due to the differential solubility parameter which decreases for the asphaltene and the oil solutions. In fact the differential solubility parameter acts as a driving force in the asphaltene precipitation formation. The variation of the solubility parameter is due to change in the nature of the liquid phase molecules, their interaction, the variation of molecular weight and the amount of polar compound in the liquid phase.

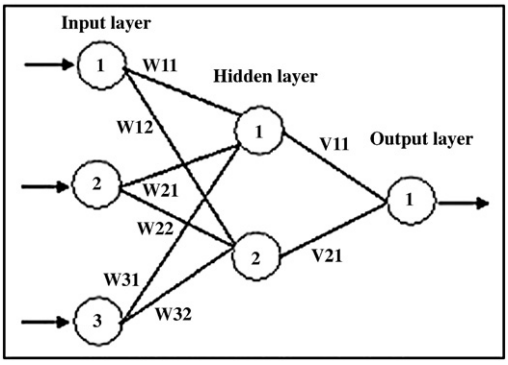

Fig. 1. A typical MLP neural network.

Fig. 2. Schematic of laboratory as phaltene precipitation.