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The Prediction of Cloud Point Temperature in Wax and Pure Paraffin Depositions by using a PSO based ANN Approach

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Abstract

Objectives: Predicting the Cloud Point Temperatures in Wax and Pure Paraffin Depositions which can help oil experts make substantial decisions to have less heavy material deposition in crude (oil). **Methods/Statistical Analysis:** In this paper, we use a PSO based ANN approach to predict the cloud point temperature of depositions, which has been designed based on the most important parameters that are related to cloud point temperature. Solvent molecular weights, solute molecular weights, and solute weight fraction are the main parameters that have been considered, while observing the cloud point temperature amounts. **Findings:** By predicting factors that make sediment happen, we eliminate or reduce the deposition of action. The modeled results show 99% for test dataset in both used depositions. **Application/Improvements:** The proposed method improves the results to achieve more precision results compared to the previous related works.

Keyword: ANN, Cloud Point Temperature, Paraffin Deposition, Wax Deposition, PSO

1. Introduction

In today's world, having artificial predictions instead of accomplishing laboratory implementations is a way forward great development. One of the main reasons for writing papers like the current one is reducing the cost of costly experiments. Furthermore, for obtaining alternative ways of trial and error tests, development of predicting laboratory work is an important motion for having artificial predictions.

Having accurate information about laboratory results, being dominant on predictive techniques and consult with experts of the target of prediction's field of study are the factors that must be considered before starting such a paper. In this study, we use an ANN method for modeling the Paraffin depositions, in which the weights of neurons are balanced base on the results of a binary PSO method.

In predicting the cloud point temperature of Wax[1], presented a predictive system based on a non-linear polynomial equation, as we can consider it as a paper which stimulated us to work on the current paper. The measure of evaluating this predictive system is announcing overall average error that is equal to 0.61%. After all of these years, so many works have been done on this issue from different perspectives. For instance[2], have studied the effect of cooling rate on the Wax precipitation in temperature of Waxy mixtures. Most of the related papers to the current paper have major purposes of either modeling or predicting the cloud point temperature of Wax. We can barely say that the main aim of writing these articles is reducing Wax depositions. Another example[3] has worked on modeling Wax deposition in crude oil. Another bold paper which has worked on the prediction of cloud point temperature of Paraffin Wax has used a

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thermodynamic model[4]. The mentioned article doesn't have proper numbers of samples, neither enough input parameters compared to our study. Also, they show that by increasing the pressure of Wax, its cloud point temperature reduces. This fact has been proved in some other studies[5,6].

2. Implementation Method

2.1 Dataset Preparation

In this study, we work on prediction of cloud point temperature in two different depositions. For the first implementation, we use the same experimental results[1–7] which has been studied to evaluate the effect of heavy paraffinic hydrocarbon components in pure and Wax paraffin deposition. Note that, the cloud point temperatures experienced in the mentioned papers are based on °F. Four different attributes are assigned as ANN inputs, which are derivative of mentioned reference. The weight fraction of solute, the amount of decane used as its solvent, the amount of heptanes used as its solvent and apparent molecular weight of solution are attributes that are illustrated in Table 1 in different amounts. The second attempt is for predicting the cloud point temperature of pure paraffin in Wax deposition. Table 2 shows the same attributes of Table 1 but with different amounts of the weight of the solution. These results are gained from[1]. Note that, 80% of input data are considered as training data and 20% of them belong to testing ones randomly.

Table 1. The input factors for predication of cloud point temperature of the solution with Eicosane (MW = 282.56) as its solute and different mixtures of Decane and Heptane as its solvents[1]

Weight Fraction Of Solute	Solvent Composition (Decane)	Solvent Composition (Heptane)	Apparent Molecular Weight of Solution
0.2	1	0	170.112
0.4	1	0	198.224
0.6	1	0	226.336
0.8	1	0	254.448
1	1	0	282.56
0.2	0.8	0.2	163.392
0.4	0.8	0.2	193.184
0.6	0.8	0.2	222.976
0.8	0.8	0.2	252.768
1	0.8	0.2	282.56
0.2	0.6	0.4	156.672
0.4	0.6	0.4	188.144
0.6	0.6	0.4	219.616
0.8	0.6	0.4	251.088
1	0.6	0.4	282.56
0.2	0.4	0.6	149.961
0.4	0.4	0.6	183.104
0.6	0.4	0.6	216.256
0.8	0.4	0.6	249.408
1	0.4	0.6	282.56
0.2	0.2	0.8	143.232
0.4	0.2	0.8	178.064
0.6	0.2	0.8	212.896
0.8	0.2	0.8	247.728
1	0.2	0.8	282.56
0.2	0	1	136.512
0.4	0	1	173.024
0.6	0	1	209.536
0.8	0	1	246.048
1	0	1	282.56

Table 2. The input factors for predication of cloud point temperature of the solution with Paraffin (MW = 480) as its solute and different mixtures of Decane and Heptane as its solvents[7]

Weight Fraction Of Solute	Solvent Composition (Decane)	Solvent Composition (Heptane)	Apparent Molecular Weight of Solution
0.2	1	0	209.6
0.4	1	0	277.2
0.6	1	0	344.8
0.8	1	0	412.4
1	1	0	480
0.2	0.8	0.2	202.88
0.4	0.8	0.2	272.16
0.6	0.8	0.2	341.44
0.8	0.8	0.2	410.72
1	0.8	0.2	480
0.2	0.6	0.4	196.16
0.4	0.6	0.4	268.12
0.6	0.6	0.4	338.08
0.8	0.6	0.4	409.04
1	0.6	0.4	480
0.2	0.4	0.6	189.44
0.4	0.4	0.6	262.08
0.6	0.4	0.6	334.72

Weight Fraction Of Solute	Solvent Composition (Decane)	Solvent Composition (Heptane)	Apparent Molecular Weight of Solution
0.8	0.4	0.6	407.36
1	0.4	0.6	480
0.2	0.2	0.8	182.72
0.4	0.2	0.8	257.04
0.6	0.2	0.8	331.36
0.8	0.2	0.8	405.68
1	0.2	0.8	480
0.2	0	1	176
0.4	0	1	252
0.6	0	1	328
0.8	0	1	404
1	0	1	480

2.2 Methodology

In this study, a Feed-forward Network is employed for modeling Paraffin Depositions. For such a network, there are one input layer, two hidden layers (less than this number of layers doesn't outperform two layers and having more than two layers doesn't make any changes in results) and one output layer. The activation function for both hidden and output layers is hyperbolic tangent sigmoid transfer function (tansig). In the input data, 1 to N-1 features are considered as inputs and the nth feature is the real output data. Figures 1, 2 depicts the ANN architecture employed in this paper.

The performance of ANN is admissible but it is not enough. One of the new ways of improving these performances is combining ANN with other optimization techniques like PSO. Actually, optimization methods can help ANN regulate the weights of neurons in a proper manner. To do so, a binary PSO is employed for setting the weights of ANN. PSO has particles which have velocities and positions. Each particle tries its best to gain the best local position. If the local position is the best position compared to the other best local position, it will be announced the best global position.

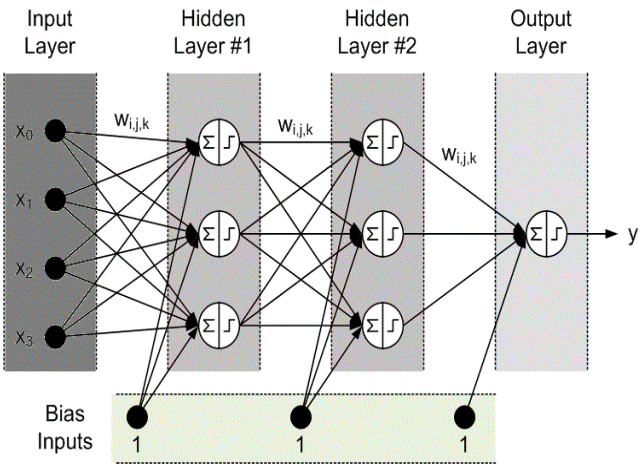

Figure 1. The architecture of a typical ANN.

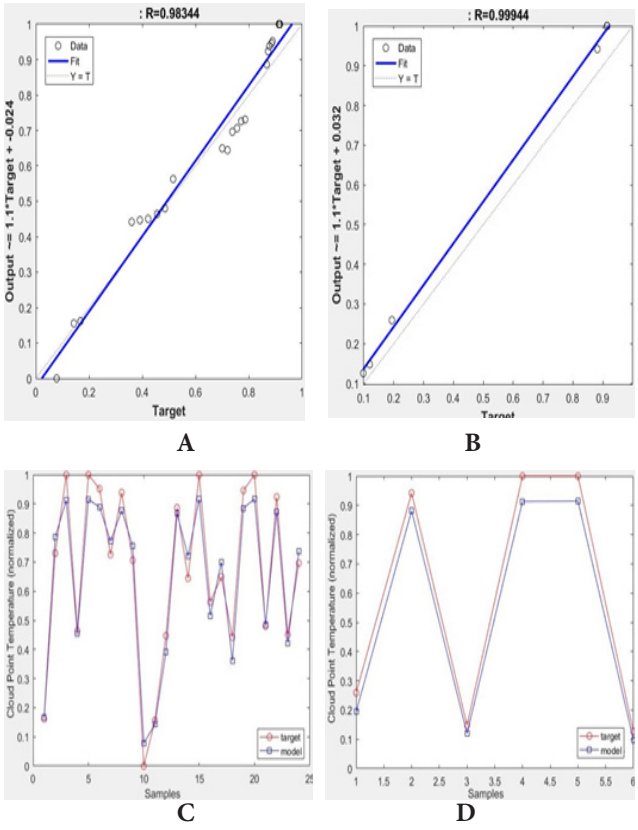

Figure 2. Comparison of experimental and model predicted values in condition 1 as we have A) as training result data set B) as testing data set results C) as MSE error plot of training data set and D) as a MSE error-plot of testing data set.

Both velocity and position of particles of this paper are calculated with Eq. (2) and Eq. (3):

$$V[i] = v[i] + c1 * rand() * (p\ best[i] - position[i]) + c2 * rand() * (g\ best[i] - position[i]) \quad (2)$$

$$Position[i] = position[i] + v[i] \quad (3)$$

The PSO particles move in a search space and come up with the optimal set of weights. When the fitness of a particle in PSO is evaluating, the weights are assigned to

the ANN which provides a better fitness of the particle. This process will be considered as personal best and if it is the best of the swarm, it would be considered as global best. The global best position after a desired number of iterations yield the optimized weights for the ANN. In general, the following steps must be passed:

Step 1: The initial parameters like population size and other mentioned ones define. P best acts as the current position of each particle. Meanwhile, the best objective function value must be calculated.

Step 2: By starting the first irritation, the particles begin to move towards the particle with best objective function value. As a result, particles have new positions in the solution space. After then, the best objective function value is announced as the g best.

Step 3: up to now, we have p best and g best in each iteration specified. G best must be rearranged in each iteration since it is the best general position in the neighborhood

Step 4: After all, the purpose of iterations is reaching the best g best that can be stopped by a final condition. In this paper, the final condition is the number of iterations which is equal to 5.

Step 5: steps 1 to 3 are repeated until the final condition is achieved.

These implementations have been executed in MATLAB 2017 b.

2.3 Performance Assessment of the Model

Evaluating the performance of every proposed model is an essential step due to presenting the accuracy of forecasted results. One of the most popular performance measures in such cases is Mean Square Error (MSE) which has been used for evaluating the performance of this paper. This measure is calculated by the following relation:

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(Y'_i - Y_i)^2 \quad (4)$$

where, Y'_i depicts a vector of n predictions and Y shows the vector of observed values corresponding to the inputs. MSE used to compute the differences between values predicted by a model and the values observed from the modeled values. On the other hand, for depicting the prediction results, the coefficient of regression, R is employed.

3. Experiments and Results

Figure 2 represents the correlation of actual results and predicted ones for our first attempt. Figure 3 shows the same correlation for pure paraffin. For both predictions, we have 97% efficiency which has been approached according to trial and error method. In implementing PSO, some initial parameters should be determined. The initial parameters for both predictions are set as:

Number of population = 280;

Number of iterations = 5;

C1 = 2;

C2 = 4 – C1;

Condition 1: The Solution with Paraffin (MW = 480) as its Solute and different mixtures of Decane and Heptane as its solvents.

Condition 2: The solution with Eicosane (MW = 282.56) as its solute and different mixtures of Decane and Heptane as its solvents.

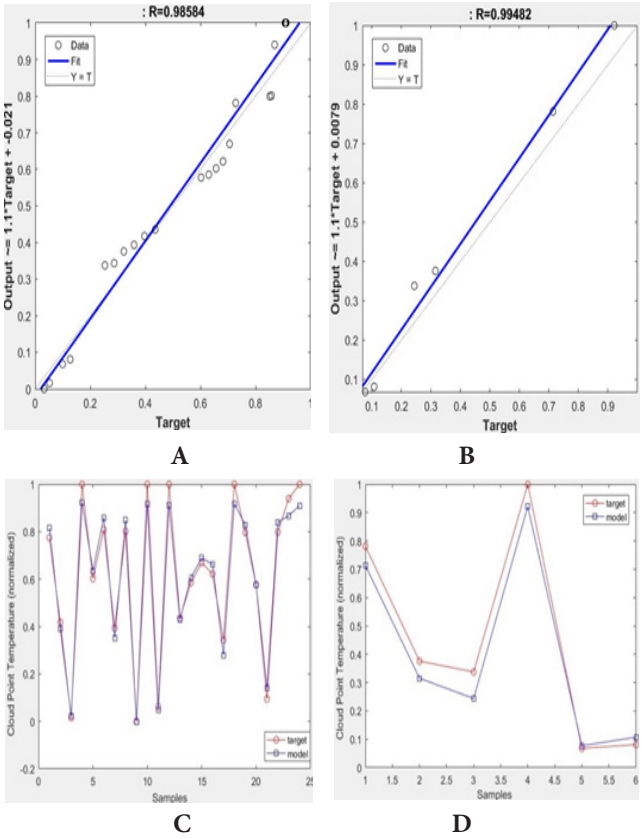

Figure 3. Comparison of experimental and model predicted values in condition 2 as we have A) as training result data set B) as testing data set results C) as MSE error plot of training data set and D) as a MSE error plot of testing data set.

4. Conclusions

In this study, by predicting the cloud point temperature of Wax and pure paraffin, we tried to have a special attitude which can help reduce the deposition of crude in a way. The prediction model is based on the solute and solution appearance molecular weights, and weight fraction of solute. As we know ANN as an acceptable predictor, we used a binary PSO algorithm to have a better balance in allocating values to its weights. In two different conditions, Wax and pure paraffin's cloud point temperature have been forecasted. In general, sixteen samples have been under study while in the best-predicted result of this studying shows 99% affinity between real and predicted values which belong to both testing datasets.

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