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PSO-Fuzzy eliminates deficiency of neuro-fuzzy in assessment of asphaltene stability

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Precipitation and deposition of asphaltene during petroleum production is a challenging problem confronted by the oil industry compromising the profitability of production fields through loss efficiency of recovery process as well as create remedial cost. Hence, developing a robust model for assessment of asphaltene stability in crude oil is necessary. ΔRI ($\Delta RI = RI - PRI$) is a novel criterion for stability determination of asphaltene in crudes. An integrated intelligent method, called neuro-fuzzy (NF) has been used in this study for estimation of ΔRI from SARA fraction data. NF develops a fuzzy inference system which is subsequently optimized by virtue of learning capability of neural network (NN). Since NN structure, embedded in NF systems is highly at risk of sticking in local minima, another improved fuzzy model is constructed and is subsequently optimized by virtue of particle swarm optimization (PSO) technique. Correlation coefficients for neuro-fuzzy and PSO-fuzzy model are found to be 0.857 and 0.9102, respectively. Comparison between constructed models show optimization of fuzzy model by virtue of PSO technique significantly improves accuracy of final prediction. Implementation of the proposed method indicate that PSO-fuzzy model is capable of accurately predicting asphaltene stability.

Keywords: Asphaltene stability, Particle swarm optimization, Refractive index, SARA fraction data

Crude oils have complex composition. Owing to intricate and complex nature of the molecular species that make up the crude oil, employment of individual molecular types for chemical identification of crude oil is not impossible. Recently, group type analysis has emerged as an alternative technique for characterization of the crude oil. SARA test is known as an example of such group type analysis which separate crude oil based on differences in polarity and solubility in four main portions namely saturate, aromatic, resin, and asphaltene^{1,2}. Among crude oil fractions, asphaltene is the most important constitute. This was attributed to their precipitation and deposition during in the early stage of oil reservoir life and later during stimulation process which has negative impact on upstream and downstream operation of oil industry³⁻⁵. It is the general consensus that asphaltene has the highest molecular weight and is the most polar fraction in crude oil⁶. They are defined as complex class of crude oils that are soluble in toluene but form precipitates in n-heptane'. Asphaltenes are originally equilibrated in crude oil at reservoir conditions through delicate balance between petroleum constitutes^{8,9}. During a variety of petroleum

recovery processes, asphaltene start to phase separate from crude oil solution once the thermodynamic conditions like pressure, temperature, and crude oil composition are varied¹⁰. Then the precipitated asphaltene gradually deposit in the form of solid particles at medium. In upstream, deposition phenomena render in formation damage through mechanism of wettability alteration and pores throat blockage¹¹. In downstream, precipitation and deposition of asphaltene cause clogging up of the production facilities as well as catalyst deactivation which considerable impact on the economy of oil industry¹². To resolve or alleviate many problems posed by these phenomena, many researchers proposed numerous predictive models to estimate the onset of asphaltene precipitation as well as its amount but because of its fuzzy nature and variety of parameters involved in its precipitations, no exact model exists^{13,14}. Hitherto, predictive models for estimating the phase behaviour of asphaltene can be divided into three different categories as follow (i) Molecular thermodynamic models¹⁵, (ii) colloidal approach16 and (iii) Models, which are based on scaling approach¹⁷.

Monitoring the asphaltene stability is one of the important issues in oil industry. Different methods are employed for assessment of asphaltene stability in crude oil¹⁸⁻²⁰. One of these techniques is using the refractive index for diagnosis of asphaltene stability. Firstly, Fan et al., recommended that difference between refractive index of crude oil (RI) and refractive index of crude oil at the onset of asphaltene precipitation (PRI) be employed as the far-reaching criterion for assessment of asphaltene stability in crude oil^{20-23} . Ideally, *RI* is computed by using Refractometer²¹. Although, the accurate value of RI can be measured with employing Refractometer, but owing to high cost of experimental implementation and also time consuming nature of aforementioned process, utilizing these techniques for practical purposes has been encountered with lots of difficulties²¹. Due to these flaws, it has become a necessity to develop mathematical model that relates the value ΔRI ($\Delta RI = RI - PRI$) to easily measure experimentally data. In current study, neuro-fuzzy model as a mathematical model is employed for making quantitative correlation between SARA fraction data and ΔRI ($\Delta RI = RI - PRI$) as asphaltene stability decisive-factor and eventually diagnosis the asphaltene stability in crude oil. Hitherto, several researchers have used neuro-fuzzy algorithm for solving their problem²⁴⁻²⁶. Neuro-fuzzy develops a fuzzy inference system that its membership functions' parameters are optimized through learning capability of neural network. Owing to neural network structure, embedded in neuro-fuzzy model, it is highly probable to stick neuro-fuzzy model in local minima. To eliminate this flaw, fuzzy model was subsequently optimized by means of particle swarm optimization (PSO) technique. Optimization of fuzzy model by PSO significantly improved precision of final prediction. Implementation of proposed method shows PSO-fuzzy provides a powerful tool for assessment of asphaltene stability of crudes. It should be mentioned that datasets employed for construction of model is collected from open source literature 27 .

Theory

Neuro-Fuzzy (NF)

Haykin defined neural network as a massively parallel distributed processor made up of simple processing units, which has a natural propensity for storing experiential knowledge and making it available for use. Neural network is a black-box brain-like model which becomes clever after learning from training data. It can use knowledge gained from past experiences and apply that knowledge to new problems and situations²⁸.

Zadeh proposed concept of fuzzy sets or fuzzy logic as an extension of Boolean logic²⁹. In fuzzy set theory, each value is a matter of degree and belongs to all fuzzy sets by a degree of membership determined by membership functions. Fuzzy set theory, which allows partial membership, is a marvelous tool for modeling the kind of uncertainty associated with vagueness, with imprecision, and/or with lack of information regarding a particular element of the problem at hand³⁰.

Artificial neural network is a black box design situation in which the process is entirely unknown, but the training data are known, while fuzzy logic is a white box design situation in which a structured human knowledge about the process exists³¹. Neurofuzzy provides a gray box situation which integrates human-like reasoning style of fuzzy systems with learning structure of artificial neural networks³². Neuro-fuzzy model constructs a fuzzy inference system such that its membership functions' parameters are adjusted through the learning structure of neural network.

Particle Swarm Optimization (PSO)

One of the major problems in data-mining modeling is optimization implementation. In 1995 Eberhart and Kennedy proposed a novel evolutionary optimization method which is called Particle swarm optimization (PSO). PSO was originally developed through imitating from social behaviour of bird flocking or fish schooling^{33,34}. Recently, this method has achieved considerable attentions a population based optimization algorithm in petroleum industry mainly due to its attractive features including a simple structure, ease of implementation, speed to achieve the desired solutions, and robustnessc35,36. In PSO's context, the population is called a swarm and its individuals (potential solutions) are called particles. Each particle in PSO has a position and a velocity. PSO is initialized with a population of random particles (solutions). The evaluation of each particle is performed through the objective function of the optimization problem, whose variables are the particle position dimensions. At each cycle the position of each particles is updated so that a particles moves to a new positions. Once the PSO is iterated until a fixed number of times or a minimum error based on defined performance criterion is achieved^{37,38}.

Results and Discussion

NF model

In first stage of this study, a neuro-fuzzy (NF) model is employed for formulating SARA fraction data to ΔRI . ΔRI could subsequently be used for judgment about stability status of asphaltene in crude oils. Figure 1 illustrates general flowchart followed in this study for determining whether asphaltene is precipitated out of solution in cruds or not. This figure is composed of a modeling box, and consequent decision on asphaltene stability status based on acquired values for ΔRI . To develop the best NF model which have had both high accuracy and good generalization, different clustering radii are assigned to NF model and performance of constructed model is assessed for test data using mean square error and correlation coefficient concepts. This information is provided in Table 1. Results indicate the best NF model is achieved when two fuzzy rules handle formulation between SARA fraction data and ΔRI . The extracted Gaussian membership functions for input data have different spread values. It means parameters of constructed fuzzy model are adjusted through the learning capability of neural network. Table 2 demonstrates constant coefficients corresponding to linear output membership functions. Figure 2 shows crossplot between measured ΔRI and predicted values. Correlation coefficient in this figure is equal to 0.857 which is a satisfying value for asphaltene stability assessment. For better understanding of success of NF model in prediction of asphaltene stability status, a comparison between measured ΔRI and predicted ΔRI versus different samples of unseen test data is provided in Fig. 3. This figure in company with Fig. 2 is evidence for robustness of NF model in evaluating asphaltene stability in crude oils.

PSO-Fuzzy Model

In next stage of study, fuzzy formulation between SARA fraction data and ΔRI was extracted by means of particle swarm optimization technique. For this purpose, PSO technique is used instead of traditional techniques for extracting fuzzy rules such as clustering methods or back-propagation based neural networks. Mean square error of prediction is employed as cost function to PSO technique. Following fuzzy mathematical formulation is used for formulating SARA fraction data to delta *RI*.

$$\mu_i(S) = \exp[-(S - m_{Si})^2 / 2\sigma_{Si}^2] \qquad \dots (1)$$

$$\mu_i(A) = \exp(-(A - m_{Ai})^2 / 2\sigma_{Ai}^2) \qquad \dots (2)$$

$$\mu_i(R) = \exp[-(R - m_{Ri})^2 / 2\sigma_{Ri}^2] \qquad \dots (3)$$

$$\mu_i(As) = \exp[-(As - m_{Asi})^2 / 2\sigma_{Ai}^2] \qquad \dots (4)$$

Clustering	No.	Mean Square	R-Square					
Radius	Clusters	Error (MSE)						
0.1	80	4.7326 e-1	0.12					
0.2	50	5.6792 e-3	0.37					
0.3	25	2.4662 e-4	0.59					
0.4	9	1.8738 e-4	0.73					
0.5	6	1.3127 e-4	0.78					
0.6	2	6.1442 e-5	0.857					
0.7	2	6.1442 e-5	0.857					
0.8	2	6.1442 e-5	0.857					
0.9	1	No optimization is done for one rule						
1	1							
Table 2 — Constant coefficients for linear output membership								
functions (MFs).								
Parameter	βο βι	β ₂ β ₂	βı					

functions (ivit s).							
Parameter MF	β_0	β_1	β_2	β_3	β_4		
MF 1	0.08606	0.0871	0.08819	0.07424	-8.577		
MF 2	-0.02393	-0.02288	-0.02136	-0.02485	2.404		



Fig. 1 — General flowchart of modeling of asphaltene stability in crude oils.

where, S, A, R and As denotes saturates, aromatics, resins, and asphaltene fraction of crude oil; μ is degree of membership; m and σ are mean and standard deviation of Gaussian membership function; and *i* refers to rule number. Following equation evaluates firing strength of each rule antecedent.

$$\mu_i = \mu_i(S) \times \mu_i(A) \times \mu_i(R) \times \mu_i(As) \qquad \dots (5)$$

The corresponding output membership function for each rule is defined as:

$$OMF_{i} = \beta_{1i}S + \beta_{2i}A + \beta_{3i}R + \beta_{4i}As + \beta_{5i} \qquad \dots (6)$$

where, β_{ij} refer to constant coefficients corresponding to each input in linear output membership function. Difference index can consequently be evaluated through the following equation.

$$\Delta RI_{est} = \frac{\sum_{i=1}^{i} \mu_i \times OMF_i}{\mu_i} \qquad \dots (7)$$

Eventually the cost function for PSO technique is defined as:



Fig. 2 — Crossplot showing correlation coefficient between measured ΔRI and predicted values. Correlation coefficient for test data using NF model is equal to 0.857 which is a satisfying value



Fig. 3 — A comparison between measured and NF predicted ΔRI for test data.

$$MSE = \frac{1}{N} \sum_{i=1}^{N} (\Delta RI_m - \Delta RI_{est})^2 \qquad \dots (8)$$

where, N is number of training data and ΔRI_m is measured values of difference index. After running the PSO algorithm, associated parameters for input and output membership functions are achieved. Extracted values for input Gaussian membership functions and extracted values for output linear membership functions are shown in Tables 3 and 4, respectively. Figure 4 shows crossplot between measured ΔRI and predicted values. Correlation coefficient in this figure is equal to 0.9102 which shows a significant improvement compared with NF model. Figure 5 provides an assessment for prediction efficiency of PSO-fuzzy model versus different samples. A comparison between neuro-fuzzy model and PSO-fuzzy model based on correlation coefficient and mean square error is shown in Fig. 6. This figure shows significant increase in accuracy of asphaltene modeling using PSO-fuzzy compared with neurofuzzy model.

Table 3 — Mean and spread of input membership functions								
Param	eter		MF1		MF2			
MF			m	б	m	б		
Satura	te	6	5.21	11.743	52.31	9.993		
Aroma	atic	1	8.32	4.529	19.84	5.367		
Resin		1	3.86	7.791	17.94	5.451		
Aspha	ltene		2.6	4.012	9.91	4.489		
Table 4 — Constant coefficients for linear output membership functions for PSO-fuzzy model.								
Paran M	neter F	βο	β_1	β_2	β_3	β_4		
MF	1	0.4229	0.4228	0.426	0.4149	-42.25		
MF	2	-0.2362	-0.236	-0.2338	-0.2366	23.65		
Predicted &RI	R ²	= 0.9102	أقجرن	M.º	-	-		

Fig. 4 — Crossplot showing correlation coefficient between measured ΔRI and PSO-fuzzy predicted values. Correlation coefficient for test data using PSO-fuzzy model is equal to 0.9102 which shows a significant improvement compared with NF model



Fig. 5 — A comparison between measured and PSO-Fuzzy predicted ΔRI for test data.



Fig. 6 — A comparison between neuro-fuzzy method and PSO-Fuzzy method versus correlation coefficient and mean square error.

Conclusion

Precipitation and deposition of asphaltene is a drastic issue in oil industry which adversely affect the flow behaviour from oil reservoirs through process facilities. In this study, a neuro-fuzzy model is employed to formulate SARA fraction data into ΔRI . ΔRI is an effective criterion for asphaltene stability determination. i.e., for $\Delta RI > 0.06$ asphaltene is stable in crudes, while for $\Delta RI < 0.04$ asphaltene is precipitated out of solution in crudes. Results of this study show by establishing two NF rules between SARA fraction data and ΔRI , the most effective and accurate model is achieved if Gaussian membership function is used for inputs and linear membership function is used for output. Crossplot between measured and predicted ΔRI values show correlation coefficient of 0.857. High value of correlation coefficient in crossplot proves superiority of NF modeling of asphaltene stability. Next stage of this study show optimization of fuzzy model by means of particle swarm optimization can significantly improve

accuracy of final prediction. Correlation coefficient of PSO-fuzzy model is 0.9102. Comparison between PSO-fuzzy and neuro-fuzzy models show superiority of PSO-fuzzy. Implementation of the proposed strategy instead of running Refractometer will reduce costs and saves time, significantly.

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