Evolving Genetic Algorithm, Fuzzy Logic and Kalman Filter for Prediction of Asphaltene Precipitation due to Natural Depletion

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ABSTRACT
The purpose of this paper is to illustrate how Fuzzy Decision Tree (FDT), which is an automatic method of generating fuzzy rules, can predict the flow rate, as a vital parameter in order to design the necessary wellhead production facilities, of an under saturated Iranian petroleum reservoir. Because of the special thermo dynamical conditions of the supposed reservoir, two very important variables consist of Temperature and Pressure, were selected as input factors. In order to develop the model of FDT, firstly, 1600 series of data were gathered and divided to two main parts which 1100 of them were utilized to build the model and the rest of them to test it. As the FDT method is strongly based on applying widely and effectively the concept of ambiguity and furthermore, to do this project more accurately and less dependent on experts' knowledge, it was decided to gain from piecewise linear membership functions (MFs) whose parameters have automatically been dedicated through calculating a very special method of possibility density function (pdf). When the process of developing the FDT was finished, there were five rules available to measure the rate of compatibility and flexibility of the model by applying the rules on testing set. The model result, 0.898 of R-square for testing set, shows that the FDT yields an acceptable result compared to other methods either practical or theoretical. In conclusion, according to the calculated result, it is possible to exploit this method for flow rate prediction field wide.

General Terms
Fuzzy Logic, Artificial Intelligence

Keywords
Asphaltene, Genetic Algorithm, Kalman Filter, Fuzzy Logic

1. INTRODUCTION
The precipitation of heavy organic materials such as asphaltene which is generally defined as a fraction of crude oil that is soluble in toluene or benzene and insoluble in low boiling alkenes such as n-pentane or n-heptane and usually dissolved in crude oil at reservoir initial condition **[4]** is one of the most problematic phenomena in upstream oil industries which results in some technical, challenging and demanding problems such as: wettability alteration in reservoir rock, diffusivity reduction and ultimately affects oil production and economical efficiency **[1, 2, 3]**. In more details, the solid precipitation particles of asphaltene forming in reservoir porous media due to pressure depletion results in reducing reservoir rock permeability which definitely threaten the economic oil recovery or noticeably increase production cost **[5]**. As a result, a numerous number of methods either practical or theoretical have been suggested to defeat this obstacle, causing many time and energy consuming problems in crude oil production and residual processing, through predicting the amount of precipitation in assistance with an exact model **[6, 7, 8]**. Although these models have been a great source in order to do effectively reservoir project modeling or making an attempt to remove the subsequent skin, a fully satisfactory interpretation is still lacking **[9].** In other words, thanks to the complicated, sophisticated and ambiguous nature of asphaltene which is caused by a large number of parameters affecting its behavior, the conventional methods, commonly including thermo dynamical models **[10, 11]**, which have been recommended in order to deal with asphaltene and its consequent struggles are not enough satisfying. This is mainly because of the accuracy which must be considered during measuring different factors involved in calculating asphaltene precipitation. Recently, the new group of asphaltene modeling methods which are based on Artificial Intelligence (AI) approaches has enormously been used by experts. Applying Fuzzy Logic (FL), firstly introduced by Lotfi A. Zadeh **[12]**, and its advantages as one of the most popular methods of the second group to model the imprecise, vague and unclear problems **[17, 18]** and their related procedures like asphaltene precipitation has recently become very noticeable. It is because of its strong abilities to deal with imprecise, vague and unclear problems. To

determine the most suitable model to find the best relationship, called fuzzy rules, between pertinent parameters such as temperature and pressure in this specific case and the target, asphaltene precipitation, it is extremely vital, critical and crucial to search for the most compatible rules. In order to generate fuzzy rule there are 3 possible rules which are (1) Through literature Survey and: (2) From Human Experts (3) Automatic Rule Generation **[13]**. Furthermore, there are some distinguish techniques to produce automatically these rules gaining from some evolutionary method like Genetic Algorithm (GA) and also, decision tree as a conventional one **[14, 15, 16]**. In the present paper, it has been made an attempt to extract exact and useful rules out of the trained part of the gathered database through applying simultaneously GA and Kalman filter. Next, these rules have been examined by testing data. Finally, the obtained results have been compared versus laboratorial reports through two different figures.

2. METHODOLOGY

2.1. Determining Membership Functions (MFs)

FL is somehow an extended version of Binary logic in which members of each collection is a matter of degree **[19]**. In other words, objects belong to a supposed set according to a special degree which is determined by a MF. The value of a degree is between 0 (completely false) and 1 (completely true) **[20].**In order to apply fuzzy logic in this case, originally, asphaltene as itself and its relevant factors, pressure (P) and temperature (T), must be characterized flexibly by appropriate membership functions. There are a large number of diverse types of MFs whose related parameters could be determined either automatically or by experts. Thanks to the having facilitation of an efficient and smooth transition between the real and natural world and the fuzzy model **[26]**, It was decided to utilize piecewise linear MFs.

$$\mu_j(x)\begin{cases} 0, & x \le \alpha_{j,1}, \\ \dfrac{x-\alpha_{j,1}}{\alpha_{j,2}-\alpha_{j,1}}, & \alpha_{j,1} < x < \alpha_{j,2}, \\ \dfrac{x-\alpha_{j,2}}{\alpha_{j,3}-\alpha_{j,2}}, & \alpha_{j,2} < x < \alpha_{j,3}, \\ 1, & x = \alpha_{j,3}, \\ \dfrac{x-\alpha_{j,3}}{\alpha_{j,4}-\alpha_{j,3}}, & \alpha_{j,3} < x < \alpha_{j,4}, \\ \dfrac{x-\alpha_{j,4}}{\alpha_{j,5}-\alpha_{j,4}}, & \alpha_{j,4} < x < \alpha_{j,5}, \\ 0, & \alpha_{j,5} < x, \end{cases} \tag{1}$$

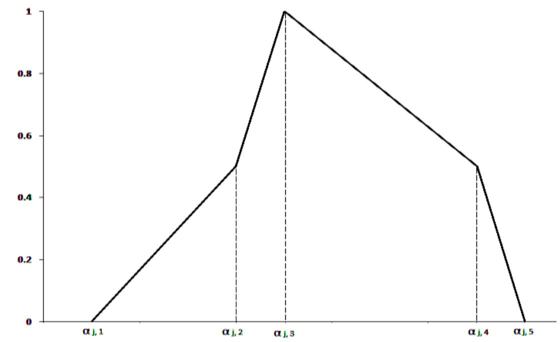


Fig.1.General form of linear piecewise membership function

In this project, in order to prevent any misinterpreting, it has been decided to utilize a special approach, proposed approach in **[21]**, to generate automatically MFs connected with P, T and asphaltene precipitation as 3 parameters which have been dealt in this research gaining from the benefits of a particular kind of Possibility Distribution Functions (pdf), referring to pdf functions as a method of MFs designing has been a topic of some related discussions since FL was put forward **[22]** which is based on Parzen window and relevant research **[23, 24, 25]**. Consequently, 201 of 275 series of data were arbitrarily selected as the training part, for MFs and rules generating, and the rest of them (74 series) were determined to test the model. Mfs of asphaltene precipitation and its affecting factors, P and T, according to the mentioned method are as below:

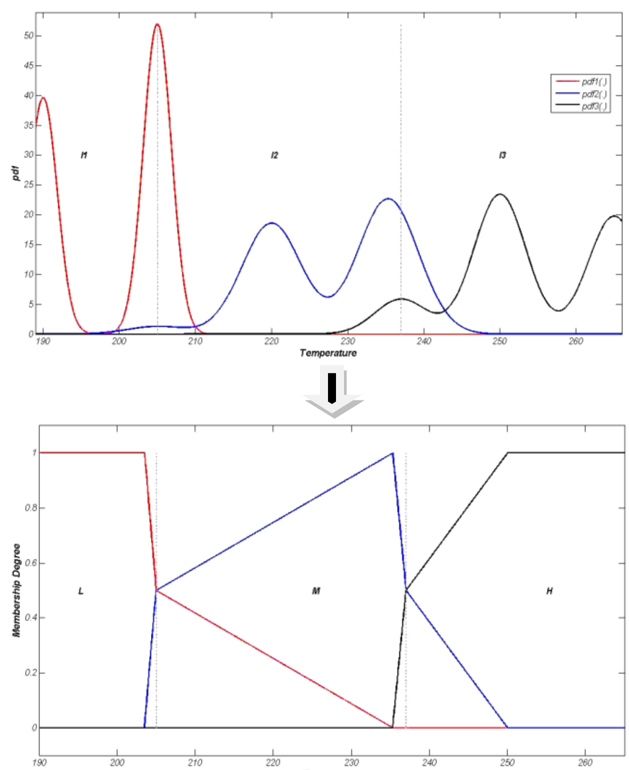


Fig.2. Estimated distribution related to intervals L, M, H for Temperature (Top) and estimated distribution related to intervals L, M, H for Temperature (Bottom)

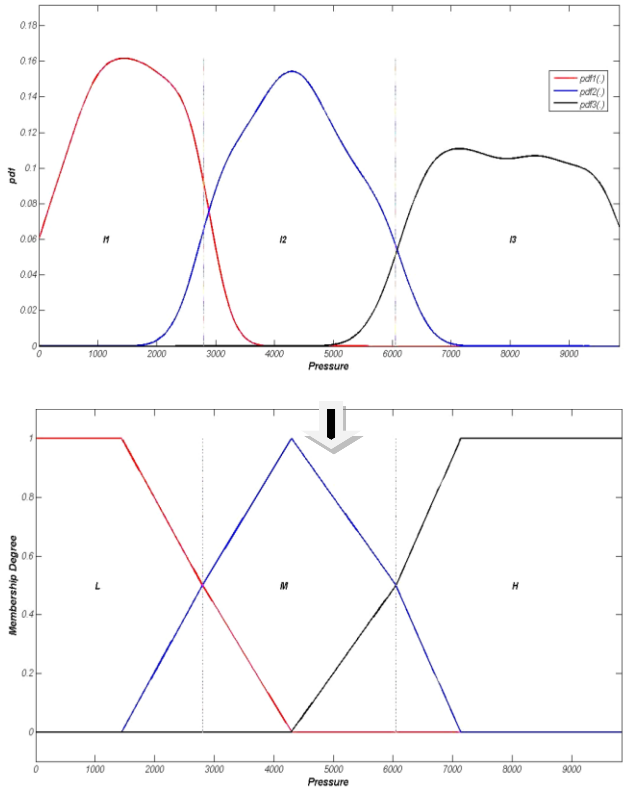
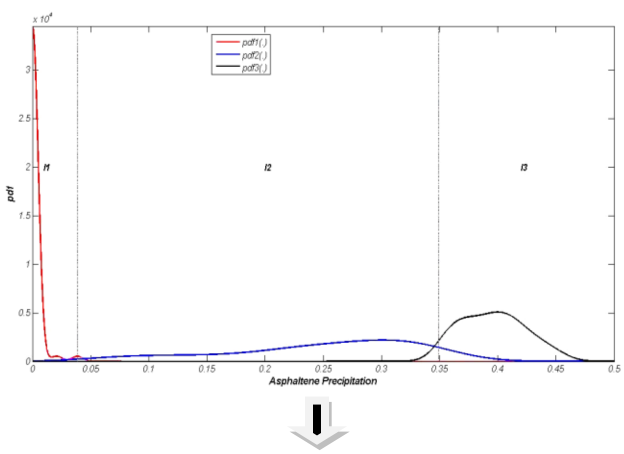


Fig.3. Estimated distribution related to intervals L, M, H for Temperature (Top) and estimated distribution related to intervals L, M, H for Temperature (Bottom)



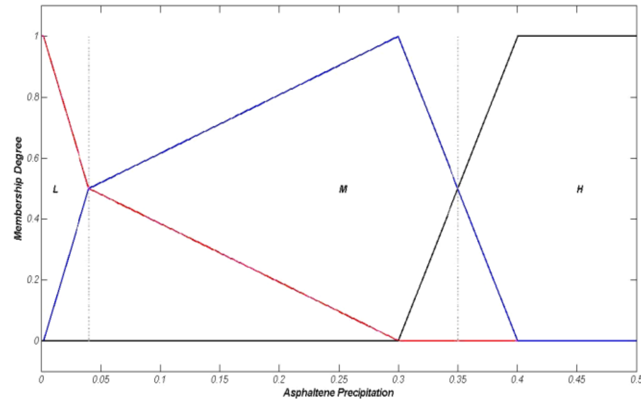


Fig. 4. General form of linear piecewise membership function (Top) and Estimated distribution related to intervals I1, I2, I3 for Asphaltene Precipitation (Bottom)

2.2. Fuzzy Rules Extracting

To conclude a well-matched asphaltene precipitation model as a highly economical, technical and drawing attention issue in upstream oil industries out of training data, dedicated by their membership degrees, constructing classification rules with linguistic terms is remarkably needed to predict truly the rate of asphaltene precipitation which can be interpreted indirectly the subsequent amount of permeability reduction of reservoir rock because of the formed skin.

In more details, it has been thought over that a fuzzy rule based system (RBS) can be taken as a solution for vital, necessary and difficult to understand reservoir engineers' challenging problems which most of them can implicitly be inferred as an aftereffect of not having a sharp model of asphaltene precipitation predicting.

In this research, thanks to the powerful ability of GA to search, a combination of Kalman filter and GA ***[29]*** has been considered to extract main, key and major rules from a large given rule base which is the most hard and time consuming aspects in constructing a fuzzy model. Generally, according to the number of linguistic terms in each MF which is 3, Low, Medium and High, the number of probable rules must be calculated. The next part to build a database is rules encoding. To do precisely this part, an index number, from the collection of {0, 1, 2}, has been dedicated to each class of attributes. For instance, the following fuzzy rule is coded as {2, 0, 1}.

IF <u>Temperature</u> is ***High*** and <u>Pressure</u> is ***Low*** then <u>Asphalten precipitation</u> is ***Medium.***

The recommended hybrid algorithm exploits a GA to look for the most prominent rules in a database and a Kalman filter to compute the relevant parameters in the output of the *i*th rule. Next step is allocating a binary value, 0 or 1, to each rule meaning the exclusion of the rule and the inclusion of the rule in the model, respectively. It means that each member of the initial population in the GA is a collection of zeros and ones that each one acts for one of the supposed rules. In addition, in the primary population there must be a binary string in which all the binary values are 1 that this member, chromosome, shows the inclusion of the all possible linguistic rules. Through operating the basic concepts of GA such as: reproduction, crossover and mutation, the GA generates the individuals (variety set of binary values or diverse combination of rules) of next generations. During the process, the related parameters of new generations found by GA are estimated by Kalman filter. New individual compatibility is evaluated by Schwarz-Rissanen Criterion (SRC) ***[27, 28]***, which is defined by

$$SRC(m) = \log(\hat{\sigma}_{\varepsilon}^{2}) + \frac{\log(n)m}{n} \qquad (2)$$

Where m indicates the number of fuzzy rules in the model, n is the number of data in the training set, and the estimated variance of model residuals is denoted by $\hat{\sigma}_{\varepsilon}^{2}$. Trying to achieve a trade-off between the accuracy and the complexity of a model was being done by this criterion.

3. RESULTS AND DISCUSSION

After implementing this method, the following results were obtained.

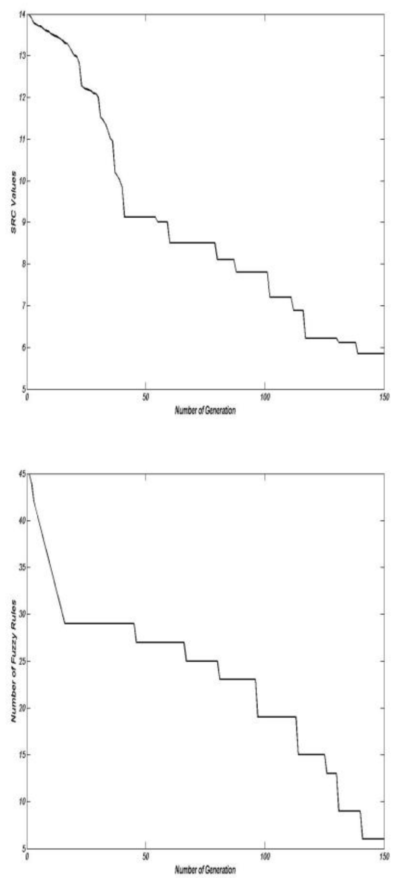


Fig.5. The SRC values and the number of fuzzy rules in the best individual in each generation.

In the last generation the highlighted and important rules extracted by the method are as below:

1) {0, 0, 0} ⇒ If ***Pressure*** is <u>*Low*</u> and ***Temperature*** is <u>*Low*</u> then ***Asphaltene precipitation*** is <u>*Low*</u>.
2) {0, 2, 2} ⇒ If ***Pressure*** is <u>*Low*</u> and ***Temperature*** is <u>*High*</u> then ***Asphaltene precipitation*** is <u>*High*</u>.
3) {1, ϕ, 2}⇒ If ***Pressure*** is <u>*Medium*</u> then ***Asphaltene precipitation*** is <u>*High*</u>. (Temperature Independent)
4) {2, 1, 1} ⇒ If ***Pressure*** is <u>*High*</u> and ***Temperature*** is <u>*Medium*</u> then ***Asphaltene precipitation*** is <u>*Medium*</u>.
5) {2, 2, 0} ⇒ If ***Pressure*** is <u>*High*</u> and ***Temperature*** is <u>*High*</u> then ***Asphaltene precipitation*** is <u>*Low*</u>.

Then, 74 series of data in the testing set were given to the supposed RBF and the consequent results were responded:

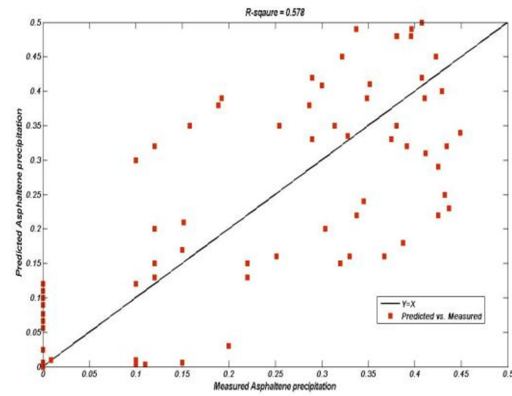


Fig. 6. The performance of predicted values of Asphaltene Precipitation vs. the measured

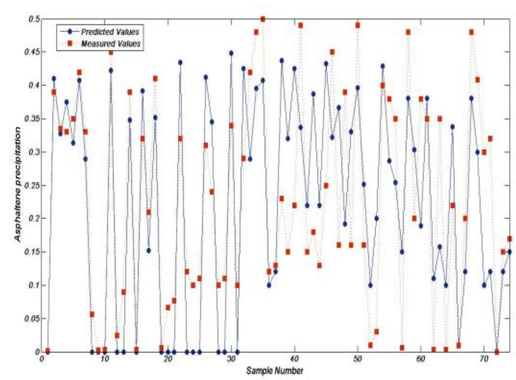


Fig. 7. The comparison between predicted and Experimental values of Asphaltene Precipitation for each sample of testing set

The simulation performance of the introduced model was evaluated on the basis of mean square error (MSE) and efficiency coefficient R^2. Prediction of asphaltene precipitation in the test phase is shown in Fig.5. It can be observed that the performance of Fuzzy model is not bad for experimental data. Fig.7 show the extent of the match between the measured and predicted asphaltene precipitation values by fuzzy model in terms of a scatter diagram.

4. CONCLUSIONS

Based on results obtained from this work, following conclusions can be drawn:

1. Artificial intelligent techniques such as fuzzy logic are powerful and reliable tools in evaluation of complex engineering systems. They can recognize the possible patterns between input and output variables and slightly successfully predict and model Asphaltene precipitation.
2. The more data you use to train your intelligent systems, the better result you get in the performance of your system. In order to make the existing model more reliable and precise we should build the prediction model again, training the model with more data points.
3. The proposed asphaltene precipitation prediction model may be combined with existing asphaltene precipitation modeling software to speed up their performance, reduce the uncertainty and increase their prediction and modeling capabilities.
4. A substitute method is to apply the genetic algorithm and kalman filter for optimizing fuzzy rules, which will be a part of our future work.

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