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# A Hybrid Neuro-Fuzzy Approach for Black Oil Viscosity Prediction

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**ABSTRACT:** In absence of PVT laboratory experiments data on representative fluid samples, it is usually difficult to choose the appropriate PVT correlations to calculate oil viscosity. This difficulty will increase when input data to PVT correlations (oil API gravity, initial gas-oil ratio, specific gravity of separator gas and temperature) vary along the flow from one section to the other in the production system. However, the accuracy of these correlations has become inadequate for the best estimations. The achievements of the Artificial Intelligent (AI) techniques alone open the door to use the hybrid system. This research focuses on the use of predictive NFuzzy model that is a result of combination of the learning capabilities of Neural Networks (NN) with the reasoning capabilities of Fuzzy Logic as a hybrid intelligent system. The proposed approach is based on clustering the PVT data into three clusters (heavy, medium and light oil) based on solution gas oil ratio. Around 500 to 2500 data points for each oil viscosity obtained from Middle East and worldwide laboratory measurements. The data were separated into two parts, 70% of data for training and the rest 30% were utilizing for testing. The present model used to estimate dead viscosity, saturated and under-saturated oil viscosity.
Based on this result, we conclude that NFuzzy exhibits a robust predictive capability for estimation of oil viscosity by providing a good match with the measured values. The additional data samples were selected to compare and validate this model.

**KEYWORDS:** Fuzzy Logic, Neural Networks, Artificial Intelligence.

## 1 INTRODUCTION

The PVT data analysis is often used in petroleum engineering computations, such as, material balance calculations, well test analysis, reserve estimates, inflow performance calculations, and numerical reservoir simulations. Ideally, the laboratory measurements of oil viscosity are the primary source of PVT data determined from laboratory studies on samples collected from the bottom of the wellbore or from the surface. However, in the absence of experimentally measured viscosity of reservoir fluids, these physical properties must be estimated from correlations. However, in the absence of such tests the use of correlations provides the only available option for the prediction of oil viscosity for field applications. Correlations are also useful as a check against laboratory results, in making estimates for experimental design and in generalization of properties.

In this work at first, the difficulty of choosing the proper correlation to calculate oil viscosity is increased when PVT data from laboratory experiments are absent. This difficulty will be more increased when input data to oil PVT correlations (oil API gravity, initial gas-oil ratio, specific gravity of separator gas and temperature) vary when calculating oil viscosity along the flow from one section to the other in the production system.

In this research, a NFuzzy approach is introduced for solving this problem. The proposed approach is based on clustering the PVT data into several groups. Using worldwide crude oil data in this work, the optimal configuration and guidelines have been developed for predicting dead viscosity, bubble viscosity, saturated and under-saturated oil viscosity. Statistical error analysis was also used to check the validity of this proposed technique.

## 2 LITERATURE REVIEW

### 2.1 EMPIRICAL CORRELATIONS REVIEW

In 65 years many empirical correlations were developed for predicting oil viscosity. These correlations predict viscosity above bubble point, at bubble point, below bubble point and dead oil viscosity at standard condition of atmospheric pressure and 60 $^{o}$F.

Beal (1946) developed a correlation by using 753 data points for determining dead oil, saturated oil and under-saturated oil viscosities at high pressure and temperature. Chew and Connally (1959) proposed oil viscosity correlation by applying 457 data points covered samples from Canada, South America, and the U.S.A. Beggs and Robinson (1975) used 600 laboratory PVT reports, including 2,533 data points, to develop saturated, under-saturated and dead oil viscosity correlations. Glaso (1980) used 45 oil samples to develop bubble point pressure, and solution gas-oil ratio. He developed also a dead oil viscosity correlation using 26 crude oil North Sea samples. Vasquez and Beggs (1980) presented a gas oil ratio, oil compressibility, and under-saturated oil viscosities correlation equation. Standing (1992) proposed correlation equations for predicting bubble point pressure, gas oil ratio, formation volume factor, oil density, oil compressibility, under-saturated and dead oil viscosities by applying a curve fitting method. Ng and Egbogah (1983) used nearly 400 laboratory PVT reports to correlate a new dead oil viscosity correlation. Khan et al. (1987) used 150 data points to estimate oil viscosity from Saudi crude oil samples. Recently, Labedi (1982) published oil compressibility, dead, saturated, undersaturated, and bubble point oil viscosities correlations using 100 oil samples from the Libya. Kartoatmodjo and Schmidt (1994) introduced correlation equations for predicting bubble point pressure, gas oil ratio, formation volume factor, oil density, oil compressibility, under-saturated and dead oil viscosities using a global data bank. Petrosky and Farshad (1995) introduced correlation equations for predicting bubble point pressure, gas oil ratio, formation volume factor, oil compressibility, saturated, under-saturated and dead oil viscosities using laboratory PVT reports from the Gulf of Mexico. Dindoruk and Christman (2001) used more than 90 PVT reports from the Gulf of Mexico regions to correlate bubble point pressure, solution gas oil ratio, formation volume factor, under-saturated isothermal compressibility factor, dead, saturated, and undersaturated oil viscosity correlation equations. Hossain et al. (2005) introduced new correlations for predicting dead, saturated and under-saturated oil viscosity for the heavy oil. Naseri et al. (2005) used 1602 data points of many Iranian oil reservoirs for predicting dead, saturated and under-saturated oil viscosity correlation equations.

### 2.2 ARTIFICIAL NEURAL NETWORKS TECHNIQUES

Elsharkawy (1998) introduced models to calculate formation volume factor, solution gas oil ratio, oil viscosity, saturated oil density, under-saturated oil compressibility, and evolved gas gravity based on radial basis function network. Input data used were reservoir pressure, temperature, stock tank oil gravity, and separator gas gravity. Elsharkawy and Gharbi (2001) developed regression method and neural network model to estimate oil viscosity based on Kuwaiti oil crude. The authors compared between the two previous models and concluded that the latter performed significantly better than the former. Osman and Al-Marhoun (2005) introduced a model to calculate brine viscosity as a function of temperature and salinity alone. Yasin and Azad (2007) introduced two new models of neural network and fuzzy logic models to predict the reservoir fluid viscosity. They used 98 data points from Iranian oil PVT reports. Sarit and Gupta (2010) developed a Artificial Neural Network model for estimating formation volume factor and bubble point pressure, solution gas oil ratio and oil viscosity based on Indian crude oil. Abbas M. Al-Khudafi (2013) used ANFIS for estimating K-values for estimating heptanes plus fractions. More than 1340 data points were extracted from 570 PVT reports based on Middle East database. Mohammad et al. (2014) developed adaptive network-based fuzzy inference system (ANFIS) approach for estimating oil bubble point pressure using commonly available field data. More than 750 data points from different geographical locations worldwide was gathered for modeling.

## 3 DATA ACQUISITION AND PROCESSING

### 3.1 DATA DESCRIPTION

In this study PVT experimental data of worldwide oil reservoirs have been used. **Table1** shows the number of data points from different regions for different oil viscosity types. The overall ranges of experimental data points used for this study are summarized in **Table2.**

*Table 1. Oil Viscosities Database*

| Data Source | Dead oil Viscosity | Bubble point Viscosity | | Saturated Viscosity | | Under-saturation Viscosity | |
|---|---|---|---|---|---|---|---|
| | Data Points | Reports No. | Data Points | Reports No. | Data Points | Reports No. | Data Points |
| World Wide** | 1180 | 169 | 169 | - | - | 210 | 210 |
| Egyptian Data | 35 | 35 | 35 | 35 | 253 | 35 | 347 |
| Middle East | 440 | 206 | 206 | 206 | 1944 | 212 | 1790 |
| Yemen | 9 | 9 | 9 | 9 | 53 | 9 | 80 |
| **Total** | 1664 | 419 | 419 | 250 | 2243 | 466 | 2427 |

** The Mediterranean Basin, Africa, the Persian Gulf and the North Sea.

*Table 2. Range of Input Data Used in This Study.*

| | Dead Viscosity | | Bubble point Viscosity | | Saturated Viscosity | | Under-saturated Viscosity | |
|---|---|---|---|---|---|---|---|---|
| | Min. | Max. | Min. | Max. | Min. | Max. | Min. | Max. |
| T($^oF$) | 68 | 342 | 75 | 342 | 75 | 342 | - | - |
| API$^o$ | 5.92 | 135 | 15 | 53 | 13.5 | 56.8 | 6 | 57 |
| $\gamma_g$ | - | - | 0.62 | 1.79 | 0 | 7.14 | - | - |
| Rs(scf/bbl) | - | - | 7.9 | 2988 | 1.53 | 7804 | 7.9 | 7804 |
| P(psia) | - | - | - | - | - | - | 1.8 | 15305 |
| Pb(psia) | - | - | - | - | 64 | 6614 | 64 | 6614 |
| $\mu_{od}$(cp) | - | - | 0.2 | 164 | 0.2 | 163.6 | 0.2 | 1387 |
| $\mu_{ob}$(cp) | - | - | - | - | 0.1 | 75 | 0.1 | 296 |

### 3.2 Data Normalization

The data is normalized to avoid numerical difficulties during the calculation. In the modeling process, the oil PVT data sets were scaled to the range between 0 and 1 as following Equ. (1):

$$Y = (X - Xmin) / (Xmax - Xmin) \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \quad (1)$$

where Y is the normalized value and X is the original data and $X_{min}$, $X_{max}$ are, respectively, the minimum and maximum of the original data. The output data need to be de-normalized to get the simulated oil PVT data and compared with measured oil PVT data.

### 3.3 Data Clustering

The purpose of clustering PVT data, increase the oil viscosity accuracy by using NFuzzy model. The oil viscosity data can be clustered manually into three groups based on solution gas oil ratio that shown in **Table3**. Clustering the input PVT data in this way will make their calculations in more easy and accurate.

*Table 3. The Most Important Parameters Range for Clustering PVT Data.*

| Characteristics | Heavy Oil | Medium Oil | Light Oil |
|---|---|---|---|
| Gas oil ratio, Rs | 0-500 | 500-1500 | 1500-3200 |

## 4 Hybrid NFuzzy Model Development

The fuzzy logic and neural networks have some disadvantages. Fuzzy Logic has a difficulty to determine the shape and the location of membership functions (MFs) for each fuzzy variable whereas the Neural Network has a problems to optimize the number of hidden layers, number of neurons in each hidden layer, learning rate and momentum coefficient. The trial and error is a difficult process to find either fuzzy rules with appropriate membership functions for FL or the number of hidden layers with their neurons for NNs. **Table4** shows advantages versus disadvantages of the NNs and FL.

*Table 4. Advantages and Disadvantages of the NNs and FL [Arnold F. Shapiro, 2002][10].*

| Technology | Advantage | Disadvantage |
|---|---|---|
| **NN** | Adaptation, learning, approximation. | Slow convergence speed, 'black box' data processing structure, slow. |
| **FL** | Approximate reasoning, quick. | Difficult to tune, lacks effective learning capability. |

To overcome these problems, the advantages of these two hybrid systems can be combined in order to avoid their disadvantages. The NFuzzy model is a result of an intelligent combination between the learning capabilities of Neural Networks and the reasoning capabilities of Fuzzy Logic as a hybrid intelligent system, proposed by **Jang**[41]. On other hand, new hybrid systems of NFuzzy is provided a better understanding about the properties of the unknown database and a better system performance with short learning times.

The NFuzzy model of adaptive network based Adaptive Neuro-Fuzzy Inference System (ANFIS), **(Jang, 2015, 1996**) is one of the most approaches for solving function approximation problems. The NFuzzy model is hybrid framework which learns the rules and membership function from data. The NFuzzy model of ANFIS is multilayer neural network associated with learning rules. The networks have capability for learning a relationship between inputs and outputs.

The NFuzzy learning employs for updating membership function parameters as a hybrid method consisting of back-propagation for the parameters associated with the input membership functions, and least squares estimation for the parameters associated with the output membership functions.

It is assumed that the rules contain the fuzzy if-then rules of Takagi and Sugeno's type (**Jang, 1993**) as follows:

IF **x** is **A** and **y** is **B** then **z** is **f (x, y)**

Where A and B are the fuzzy sets in the antecedents and z=f(x, y) is a crisp function in the consequent. Usually f(x, y) is a polynomial for the input variables x and y. When f (x, y) is a constant, a zero order Sugeno fuzzy model is formed which may be considered to be a special case of Mamdani FIS ( **Jang**, **2015**) where each rule consequent is specified by a fuzzy singleton. If f(x, y) is taken to be a first order polynomial a first order Sugeno fuzzy model is formed. For a first order two rule Sugeno fuzzy inference system, the two rules may be stated as:

$$\boldsymbol{Rule\ 1}: If\ \ x\ is\ A1\ and\ y\ is\ B1\ then\ \ \ f1 = p1x + q1y + r1$$

$$\boldsymbol{Rule\ 2}: If\ \ x\ is\ A2\ and\ y\ is\ B2\ then\ \ \ f2 = p2x + q2y + r2$$

Here NFuzzy proposed by Takagi and Sugeno ( **Jang**, 2015) is used. In this inference system the output of each rule is a linear combination of the input variables added by a constant term. The final output is the weighted average of each rule's output. The corresponding equivalent NFuzzy structure is shown in **Figure (3-2).**

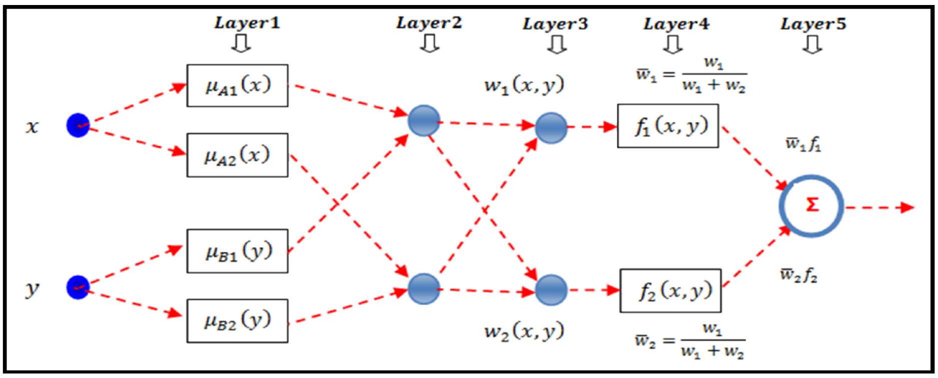


*Fig. 1. The Basic Architecture of NFuzzy.*

The basic architecture is shown in **Figure1** having a total of five layers **Ulas, 2009**. Subtractive clustering is an effective approach to estimate the number of fuzzy clusters and cluster radii in Sugeno fuzzy interference system (**Jarrah and Halawani, 2001**). Therefore, all MFs for input and output were extracted by means of subtractive clustering. Clustering radius is a functionally critical design parameter that has a significant role in FIS construction. It could vary between the range of 0 and 1. Specifying a smaller cluster radius will usually yield more and smaller clusters in the data (resulting in more rules). A large cluster radius yields a few large clusters in data (**Chiu, 1994**).

The ANFIS with Subtractive Clustering (ANFIS-SC) was used to generate a FIS by first applying subtractive clustering on the data. This is accomplished by extracting a set of rules that models the data behavior by first using the ***genfis2*** function to determine the number of rules and antecedent membership functions and then using linear least squares estimation to determine each rule's consequent equations.

## 5 Statistical Error Analysis

Statistical and graphical error analyses were used to check the accuracy and performance of those developed techniques in this study. The accuracy of the correlation relative to the actual value is determined by using various statistical means. The criteria used in this study were average percent relative error, average absolute percent relative error (AAPRE) and minimum/maximum absolute percent relative error, the correlation coefficient (CC), and the root mean square error (RMSE).

## 6 Result and Discussion

In this stage of study, ANFIS was used to get the optimum configuration for estimating oil viscosity based on earlier database. The ANFIS with Subtractive Clustering (ANFIS-SC) was used to generate a FIS by first applying subtractive clustering on the data. This is accomplished by extracting a set of rules that models the data behavior by first using the ***genfis2*** function to determine the number of rules and antecedent membership functions and then using linear least squares estimation to determine each rule's consequent equations.

Subtractive clustering method used to generate the input membership functions (***Gaussian***) and output membership functions (***Linear***). A hybrid optimization method which combines least squares estimations with back-propagation was used to adjust the membership functions' parameters.

In order to find the optimum radii and number of clusters, firstly different radii were proposed to estimate each black oil properties. Then, the optimal clustering radius was specified by achieving the lowest AAPRE and the highest correlation coefficient (CC). **Figure2** depicts how an optimal radius of black oil viscosity ANFIS model was determined. Accordingly, specification of clustering radius of each black oil properties types is shown in **Table5,** the ANFIS model's error reaches its minimum value. Each input was bunched into a number of Gaussian clusters. Output membership functions were linear equations.

To avoid overfitting, test data were input to NFuzzy model as checking data. The NFuzzy model was trained using training data with 20 epochs and zero error tolerance. After training the NFuzzy model, the test data were input to the constructed model. **Table5** shows the number of cluster and optimal cluster radii for NFuzzy model.

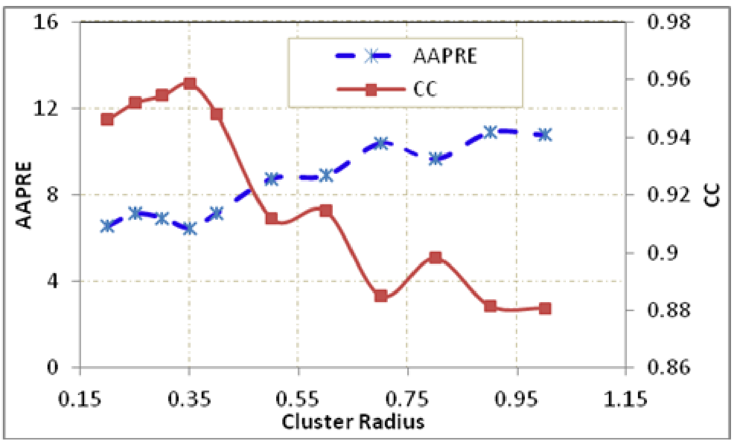


***Fig. 2. Optimal Cluster Radii for ANFIS-SC Model of Dataset.***

*Table 5. Optimal Radii of Oil Viscosity Dataset for NFuzzy model.*

| **Oil Property** | | **Heavy Oil** | **Medium Oil** | **Light Oil** |
|---|---|---|---|---|
| **Dead Oil Viscosity** | Radii | 0.17 | 0.15 | 0.14 |
| | No. of Cluster | 5 | 29 | 32 |
| **Saturated Oil Viscosity** | Radii | 0.23 | 0.31 | 0.25 |
| | No. of Cluster | 23 | 4 | 29 |
| **Under-saturated Oil Viscosity** | Radii | 0.25 | 0.58 | 0.2 |
| | No. of Cluster | 6 | 3 | 22 |

The developed NFuzzy hybrid was used for determining the different black oil viscosity. The statistical accuracy analysis is also applied to check the performance of this technique according to measured data as shown in **Tables 6 through 8**. The crossplot plot results of different oil viscosity types are shown in **Figures 3** through **5**.

## 7 VALIDATION

In order to validate and examine the reliability of this model, the hybrid NFuzzy model was applied to predict of black oil viscosity using the new available data from Yemeni oil field. **Table9** summarizes the results of statistical error analysis of those data samples.

To more check the validity and applicability of this model, a measured data are compared against the predicted results. Here, three examples (oil A, oil B and oil C) were shown**. Figure 6** shows the comparison between the actual and predicted oil viscosity result. Also, **Figures 7** through **9** shows that an excellent agreement was found between the measured and the predicted oil viscosity values when both plot versus pressure.

*Table 6. Statistical Accuracy of Nfuzzy for Dead Oil Viscosity*

| | Heavy oil | | Medium Oil | | Light Oil | |
|---|---|---|---|---|---|---|
| | Abs Error | Rel. Error % | Abs Error | Rel. Error % | Abs Error | Rel. Error % |
| Maximum | 62.74 | 317.54 | 42.14 | 838.69 | 37.98 | 9314.56 |
| Minimum | 0.08 | 0.82 | 0 | 0.01 | 0 | 0.06 |
| Average | 10.70 | 56.69 | 5.52 | 72.07 | 1.11 | 62.09 |
| RMSE | 84.98 | | 135.79 | | 296.35 | |
| CC | 0.556 | | 0.742 | | 0.617 | |

*Table 7. Statistical Accuracy of Nfuzzy for Saturated Oil Viscosity*

| | Heavy Oil | | Medium Oil | | Light Oil | |
|---|---|---|---|---|---|---|
| | Abs Error | Rel. Error % | Abs Error | Rel. Error % | Abs Error | Rel. Error % |
| Maximum | 28.20 | 722.69 | 7.76 | 346.24 | 0.12 | 81.89 |
| Minimum | 1.29E-3 | 9.27E-2 | 2.33E-4 | 2.30E-2 | 4.82E-8 | 4.82E-5 |
| Average | 1.30 | 65.24 | 0.33 | 28.77 | 0.01 | 6.87 |
| RMSE | 86.01 | | 38.19 | | 16.61 | |
| CC | 0.969 | | 0.684 | | 0.860 | |

*Table 8. Statistical Accuracy of Nfuzzy for Under-Saturated Oil Viscosity*

| | Heavy Oil | | Medium Oil | | Light Oil | |
|---|---|---|---|---|---|---|
| | Abs Error | Rel. Error % | Abs Error | Rel. Error % | Abs Error | Rel. Error % |
| Maximum | 31.48 | 239.79 | 4.28 | 294.96 | 0.11 | 37.07 |
| Minimum | 5.29E-4 | 1.44E-1 | 3.25E-4 | 3.58E-2 | 4.50E-8 | 3.62E-5 |
| Average | 1.11 | 26.91 | 0.18 | 23.54 | 0.004 | 1.31 |
| RMSE | 37.90 | | 32.58 | | 5.41 | |
| CC | 0.996 | | 0.846 | | 0.983 | |

*Table 9. Statistical Accuracy of Oil Viscosity*

| | Expert | | NFuzzy | | PSONN | |
|---|---|---|---|---|---|---|
| | Abs Error | Rel. Error % | Abs Error | Rel. Error % | Abs Error | Rel. Error % |
| Maximum | 1.47 | 120.49 | 0.53 | 39.0 8 | 0.08 | 9.16 |
| Minimum | 0.02 | 1.55 | 0 | 0 | 0 | 0 |
| Average | 0.26 | 38.50 | 0.03 | 5.54 | 0.01 | 0.95 |
| RMSE | 47.91 | | 8.73 | | 1.70 | |
| CC | 0.906 | | 0.992 | | 1.00 | |

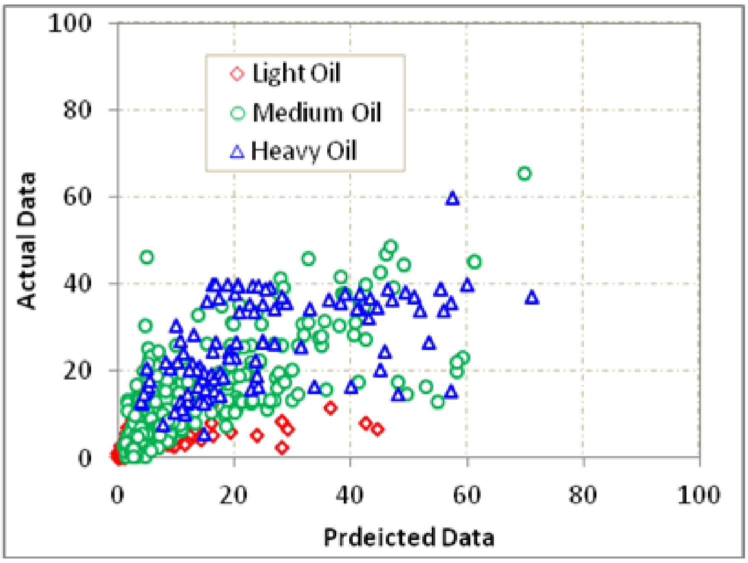


*Fig. 3. Crossplot of Dead Oil Viscosity.*

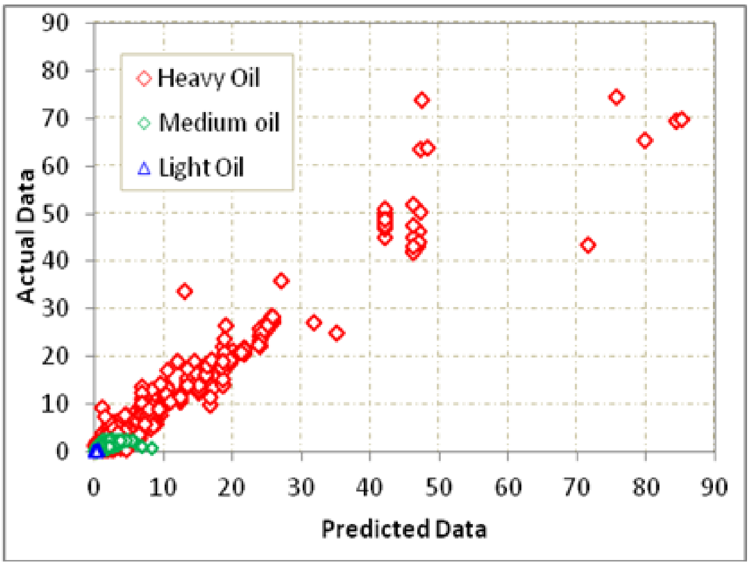


*Fig. 4. Crossplot of Saturated Oil Viscosity.*

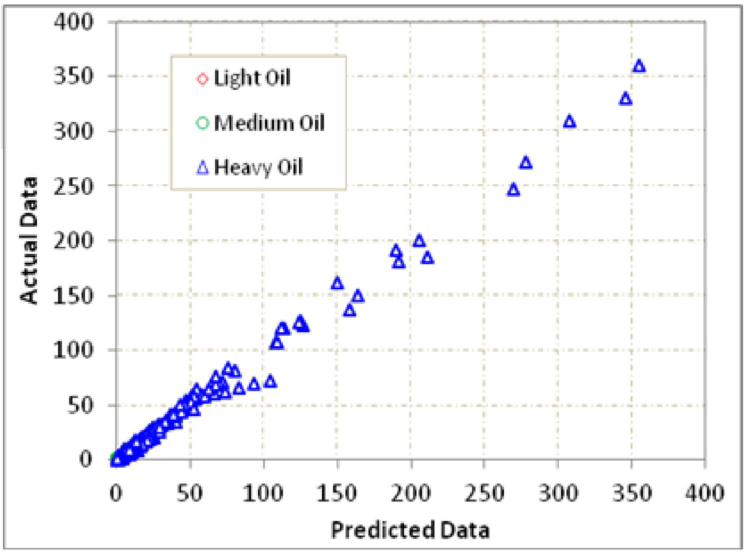


*Fig. 5. Crossplot of Under-Saturated Oil Viscosity.*

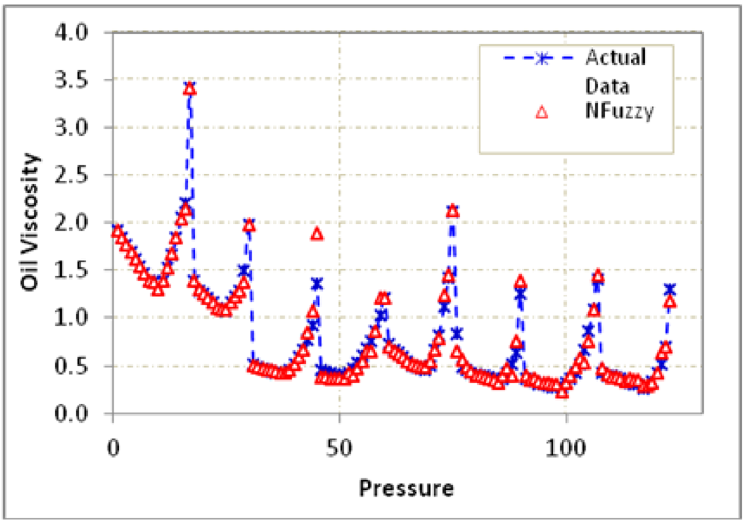


*Fig. 6. Comparison between Actual and Predicted Oil Viscosity Values.*

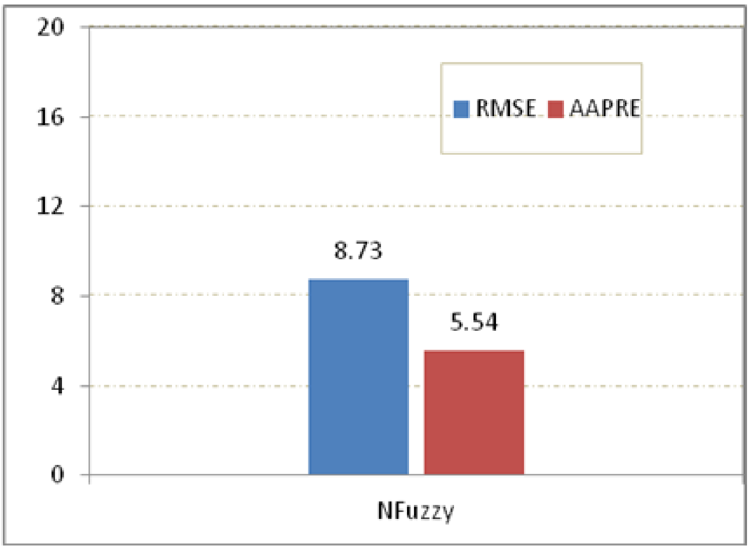


*Fig. 7. Shows the RMSE and AAPRE of Oil Viscosity.*

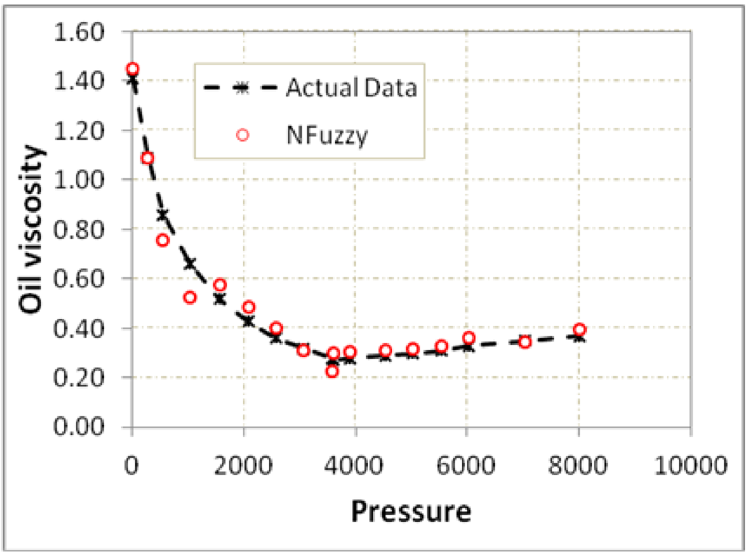


*Fig. 8. Actual and Predicted Oil Viscosity Data against Pressure (Oil A).*

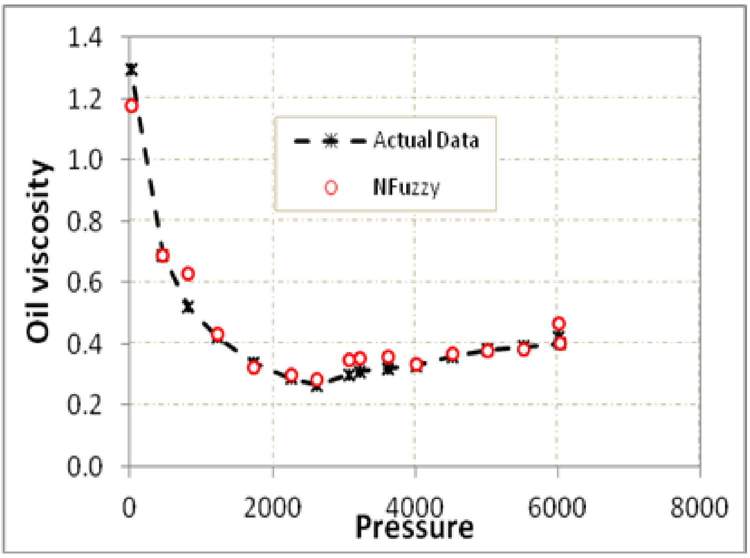


*Fig. 9. Actual and Predicted Oil Viscosity Data against Pressure (Oil B).*

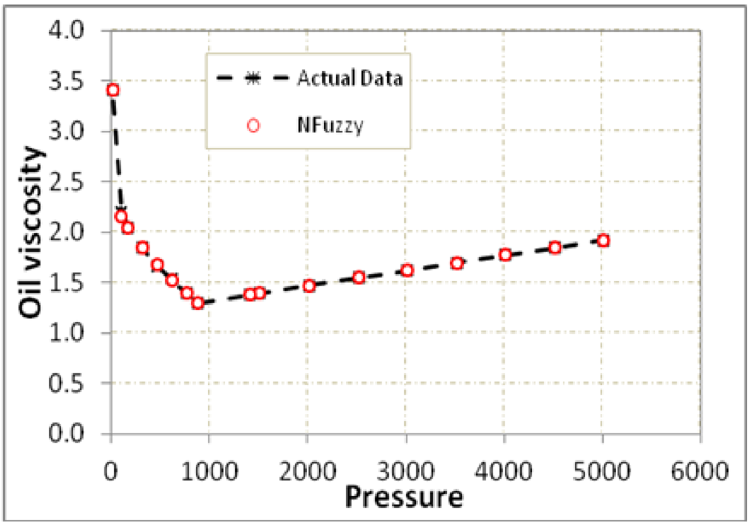


*Fig. 10. Actual and Predicted Oil Viscosity Data against Pressure (Oil B).*

## 8 CONCLUSIONS

The following conclusions can be made from this study:

- New approach for estimating oil viscosity is introduced based on NFuzzy and data clustering.
- The proposed guidelines are very useful, effective and can overcome the oil viscosity calculations weakness caused by oil viscosity variation along flow from one section to the other in the production system.
- The proposed approach can be programmed and incorporated in any simulator to improve the accuracy of oil viscosity and should be taken in consideration into any oil viscosity calculation.
- Intelligent techniques are powerful tools which overcome incompleteness, imprecise and uncertainty existent in reservoir parameters.
- The hybrid models showed superior performance with the highest correlation coefficients, and lowest root mean square errors.

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