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Neural Networks Models for Estimation of Fluid Properties

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Abstract

Fluid viscosity is one of the most important parameters necessary to establish reservoir production and economical potential. Until the appearance of NMR techniques in the oil industry, oil viscosity determination was limited to laboratory tests and correlations with API gravity. Nuclear Magnetic Resonance is a technique based on the magnetic behavior of hydrogen nuclei. This behavior is the consequence of fluid properties, as viscosity and density, and its interactions with its surroundings. The use of NMR signals for estimation of fluid viscosity has been based mainly on correlations with single NMR parameters as logarithmic (T2log) and geometric averages (T2geo). However, qualitative analysis of NMR T2 distributions indicate that changes on NMR patterns translate on changes on viscosity, that sometimes are not reflected on the averages used. This fact brought the idea of developing a multivariable model, which considers the use of all points of the NMR T2 distribution to enhance fluid properties estimation. The use of neural network technique was identified and several models were developed. The models were developed using the T2 distribution and the cumulative T2 distribution. The model constructed based on the cumulative T2 distribution, showed a better prediction of oil viscosity, incrementing the correlation with real values from 64% using the T2log correlation to 87% with the neural network. This work was done on 24 oil samples from different Venezuelan fields covering a range from 6 to 700 cP. An additional model was developed selecting 15 samples from the same field covering a range from 25 to 72 cP. Comparing the results of the model vs. the estimation through T2log correlations, the prediction was enhanced from 89% to 99%, creating an excellent model for fluid viscosity determinations through NMR signals.

Introduction

Reservoir formation evaluation is based on estimation of properties as porosity, permeability and fluid saturation. This properties together with fluid properties, as viscosity and density, are used in the determination of the reservoir productivity. Well logs have been successful in the determination of porosity and fluid saturation, however, determination of permeability, viscosity and fluid density are still limited to the use of correlations or laboratory studies.

Fluid viscosity is highly important on the determination of fluid mobility inside the reservoir, which defines the reservoir productivity index. Previous studies have shown that viscosity can be estimated through NMR studies[1,2]. However, viscosity estimation is still limited to the analysis of few parameters of the NMR signals, as the logarithmic average (T2log). On the other hand, qualitative analysis of NMR results indicates that there is a high influence of viscosity on the NMR T2 distribution shape, since different oil components are distributed along the T2 distribution.

For this reason, the idea of use non-linear multivariable techniques is proposed to use all the information content in the T2 distribution curve on fluid properties estimation.

Methodology

NMR data was taken on oil free samples with a Maran Ultra* equipment for an interecho time of 300μs. NMR decay signal was processed to obtain NMR T2 distribution what was the base of the present study. Oil samples were selected from different fields of Venezuela, with oil viscosities varying from 7 cp to 700 cp (24 samples). Cumulative and derivative T2 distributions were determined, to assess the benefit of preprocessing the signal before doing the neural network analysis.

The non-linear study was divided in two steps, data visualization and neural network modeling. Data visualization allows two study the relationship between points. The algorithm used can project all the data in two dimensions, keeping the geometrical properties of the original space.

The clustering algorithm was applied to the T2 distributions of the samples, in the original, cumulative and derivative form. This exercise was made to identify which of the curve's form can provide more information about the fluid properties studied.

* Universal's system

After identifying the more appropriate analysis, neural networks models were developed to estimate fluid properties. These models were adjusted changing the neuron numbers until obtaining the best data estimation.

Additionally, specific models were created for oil samples from the same field with the idea of verifying if a specific model from oils of the same origin could improve property estimation. This was done with study field samples, which had 15 samples available.

Data visualization Results Analysis

Data visualization analysis of T2 distribution (see figure 1) in its different forms, original, derivative, cumulative and short times, allows to identify the most appropriate way to generate neural network models from NMR data to estimate oil viscosity and API gravity. This analysis was done considering the whole range of viscosities studied and the oils samples for the study field, for both studied properties, viscosity and API gravity.

In this study, we expect that points with similar properties are located in the same part of the graph, while dissimilar samples should appear in different areas. On the other hand, overlapping of several points with different properties shows that the analysis is not appropriate.

Data visualization analysis for viscosity data in the full range:

Several projections in two dimensions for different T2 distribution forms were evaluated, including viscosity values for each sample. This analysis allows to observe how the distribution of samples changes depending on the T2 distribution form used.

In figure 2 we can see 3 zones, where the first has the highest viscosity points, the second has the medium viscosity points and the third has the low viscosity points. However, we can see that the three areas are not very well defined, being necessary to force the limits between viscosity groups.

In figure 3, cumulative form of T2 distribution, 4 zones are determined, where the first one has the highest viscosity points, the second has the lowest, and third and fourth has the middle viscosity points. As we can see in this figure, these 4 zones have good differentiation what suggests that cumulative T2 distribution is an excellent option for multivariable viscosity model estimation.

Data visualization analysis for viscosity data from the study oil field:

The same previous analysis was also done for all samples from the same oil field.

Based on the above information, visualization analysis was done for the study samples. In this case, a similar behavior was seen for the original and cumulative T2 distribution form (see figure 4 for the original form), identifing 3 zones. Zone 1 for the highest viscosity samples, zone 3 for lowest and zone 2 to the middle viscosity samples, what indicated that both forms of the curve are either appropriate for the analysis of the study field.

Data visualization analysis for API gravity data in the full range:

The above analysis was done similarly for API gravity. Data visualization for the original T2 distribution identified 3 zones, where 2 of them are not very well differentiated. The derivative form of the curve does not shows good results, in which zones present overlapping, resulting in a poor differentiation. The cumulative form of T2 distribution shows more differentiation, where zone 1 has the low API values, high values are in zone 2, while middle API gravity values are in zone 3. However, the cumulative form still shows some overlapping between points, what does not allow us to concluded which of the forms, original or cumulative, is the most appropriate for the API gravity study.

Data visualization analysis for API gravity data from the study field:

Data visualization analysis for the API gravity data samples from the study field, using the T2 distribution in its original and cumulative form, shows good differentiation with 3 zones: one close to 24 API, other between 25 and 26 API, and finally, one with values higher than 27 API. Concluding again, that both forms of the curve could be useful for API analysis in the study field.

Neural Networks Results

Results from neural network models for the viscosity and API gravity estimation show to be very useful for fluid properties estimation using NMR data, since correlation factors between real and estimated values are higher than 95%.

Previous projection studies showed that original and cumulative form of T2 distributions are the best approach to multidimensional analysis, and so, were selected for model generation.

Neural networks models were generated in the full range of viscosities and in the study field, for both properties, viscosity and API gravity.

Neural Network Model from the viscosity data for the full range:

Results of the viscosity model for the full range, using the original T2 distribution shows a good correspondence between estimated values and the real values. The correlation coefficient between the estimated and real values is 95% for all the data, and 97% for the data used for validation (non trained). However, samples number 11 and 20 are very different from the real value, where sample number 11 has a negative value, which has no physical meaning. For this reason, this model is not appropriate.

Figure 5 shows the sensitivity study of the network. This study represents the contribution of each input value (in this case, characteristic times) to the output value. Here we can't see a particular important segment from the T2 distribution, because all the values seem to have the same relevance for the model.

Figure 6 shows neural network model results using cumulative T2 distribution. In this case, the average error decreases significantly compared with the previous case (original T2 distribution). Another advantage of the model is that all estimated values were positives, what is very important for properties prediction.

The model makes an excellent estimation of all the data studied, where the resulting coefficient is near 100% for all the data or the validation data. The network sensitivity for this model is the same than in the previous analysis, where there isn't an important segment of T2 distribution for property estimation.

Neural Network models for the viscosity data from the study field:

Results for the model, using the original shape of T2 distribution, shows a very good correlation between estimated and real viscosity values.

In figure 7 we can see that neural network sensitivity for each point in T2 distribution curve, in this case there are 3 curve zones which have more influence on the training, in which short times have not importance. This could be related to the fact that oils from the study field are medium API gravity (medium viscosity), where medium and large relaxation times are expected. Additionally, this figure shows the T2 distribution curve of two of the study field's oil, where we can see the more sensitivity zones are related to the zones with more NMR information from the oils.

The next figures show the same analysis of the cumulative T2 distribution curves from the study field. Data visualization analysis of this curves showed than similar results to the original shape of T2 distribution must be expected. The important difference between them, is than the cumulative model requires less neurons to reach a good estimation. Having less neurons implies a more simple model which is more general. Figures 8 show than the estimated values obtained for this models are very good showing correlation coefficients of 99%. Again, in this case the figure 9 shows that exists a higher sensitivity in the intermediate zone of the distribution.

Neural Network models for API gravity data, using the full range:

Neural networks models were also determined for API gravity. Results using the original of T2 distribution, shows excellent results in all the API gravity range 16 to 40 API (R^2=0.99 and 0.97 for non-trained).

For the model sensitivity all points contributed to model generation.

The same analysis was done using the cumulative form of T2 distribution. In this case we have a good correlation, but the error in some cases seems to be greater than for the original form.

Here, there is a decreased correlation coefficient compared with the previous case (R^2=0.98), especially in the not trained values (R^2=0.94). These results concluded the expected from the visualization analysis, where both models can make a good estimation for API gravity. Again, all T2 distribution points are necessaries.

Neural Network models for API gravity from the study field:

Model results for API gravity of study field showed that estimated errors are very low (lower than 4%), result that guaranties good property estimation.

In the sensitivity analysis for this case we can't detect specific areas, concluding that the points are important for the API gravity estimation.

A similar analysis is used for the cumulative of T2 distribution. This analysis shows a better property estimation, where the error is under 1%. Correlation coefficients for all the data and for the validation data are excellent for the API gravity estimation.

Conclusions

- Multivariable analysis of NMR signals is very much useful for estimation of fluid properties.
- Visualization analysis allowed to identify that the original and cumulative form of the T2 distribution are the most appropriate form of the curve for multidimensional analysis.
- Neural network models improved estimation of fluid properties up to 99% between real and estimated values.
- Specific models for study field showed to be very robust with low levels of error (<3%) and with high correlation factors (>99%).

Recommendations

- It is recommended to use neural networks analysis of NMR signals for properties estimation.
- Sensitivy analysis of neural networks, could be useful to determine which areas of the T2 distribution have more information about certain properties, what could be used in improvements of data acquisition or data analysis.

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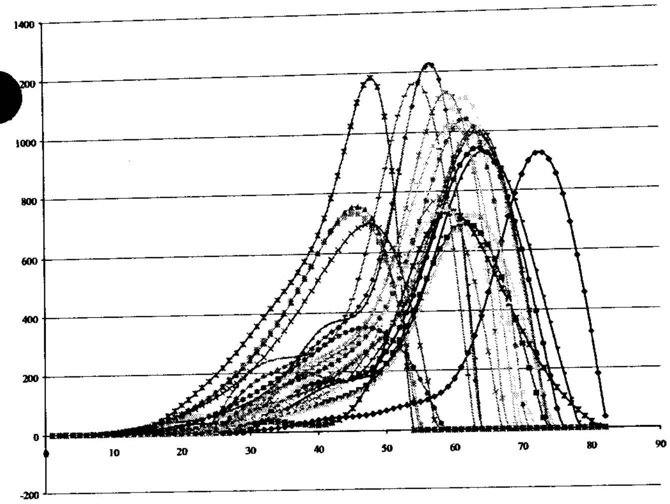

Fig. 1 – Representation in two dimensions of visualization analysis of T2 distribution for viscosity data.

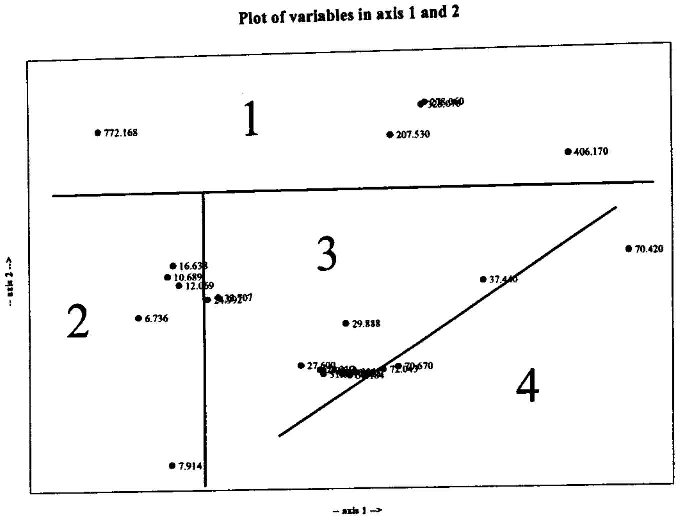

Fig. 3 – Representation in two dimensions of visualization analysis of cumulative T2 distribution for viscosity data.

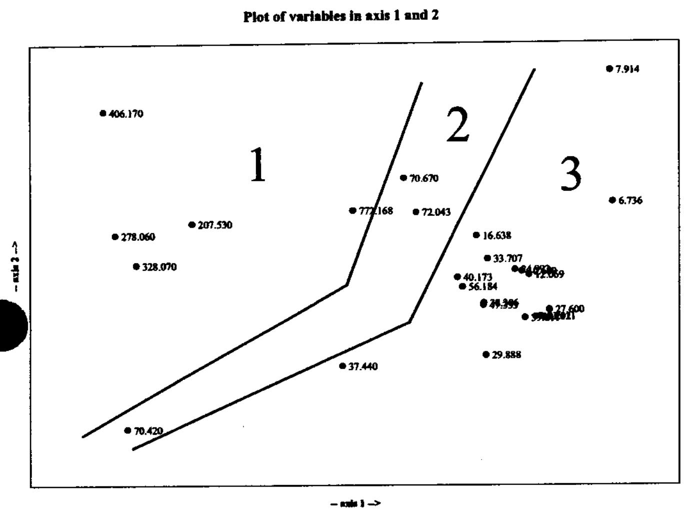

Fig. 2 – Representation in two dimensions of visualization analysis of T2 distribution for viscosity data.

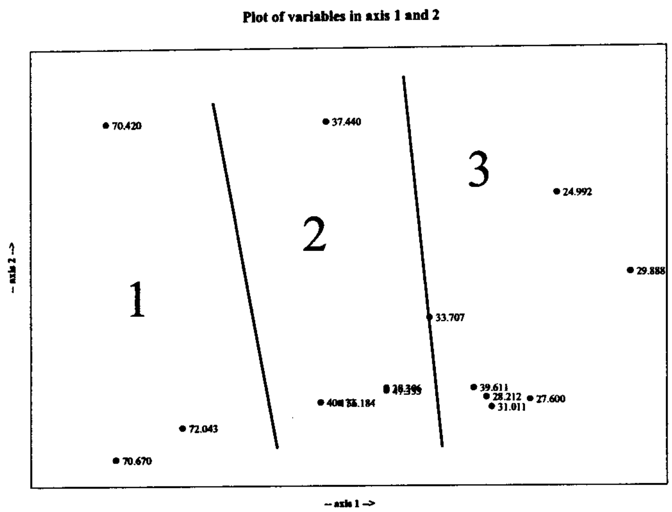

Fig. 4 – Representation in two dimensions of visualization analysis of T2 distribution for viscosity data of the study field.

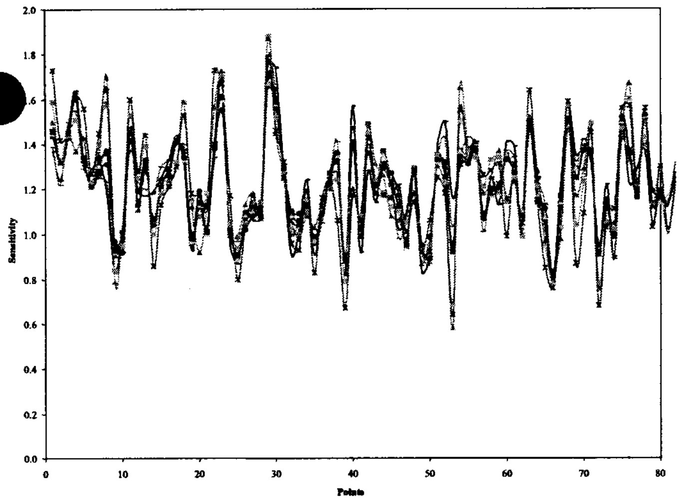

Fig. 5 – Sensitivy of the neural network for the analysis with the T2 distribution of the full range viscosity data.

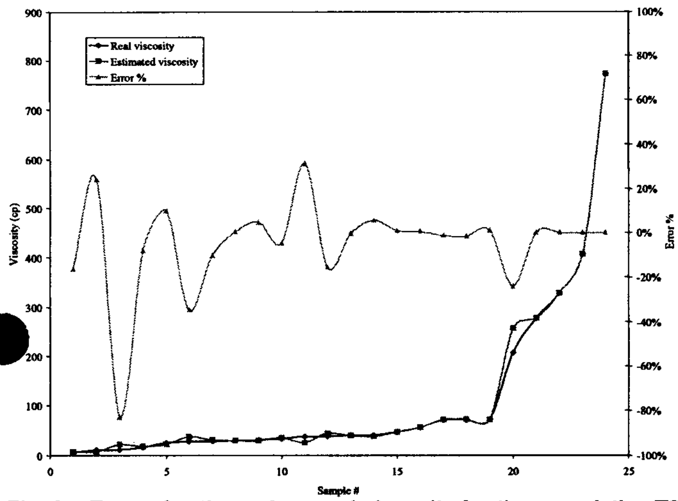

Fig. 6 – Error of estimated vs. real viscosity for the cumulative T2 distribution analysis of the full range viscosity data.

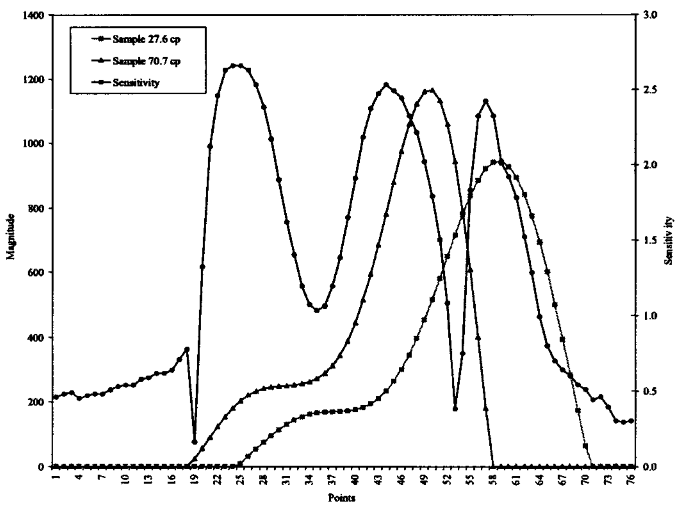

Fig. 7 – Sensitivy of the neural network and raw NMR data for the analysis with the T2 distribution of the study field viscosity data.

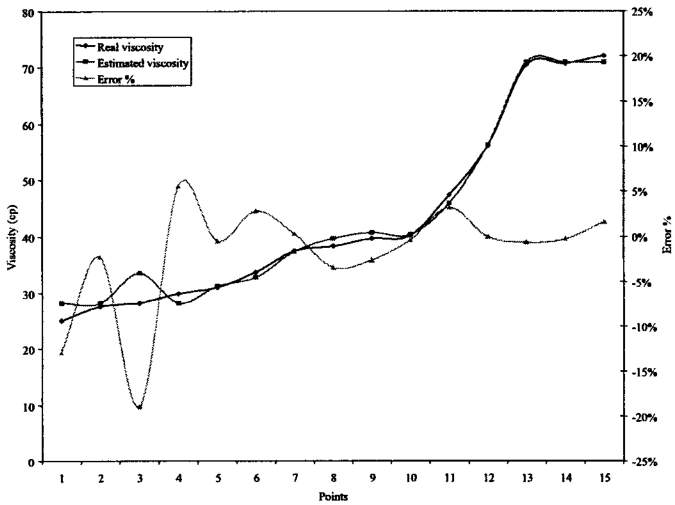

Fig. 8 – Error of estimated vs. real viscosity for the cumulative T2 distribution analysis of the study field viscosity data.

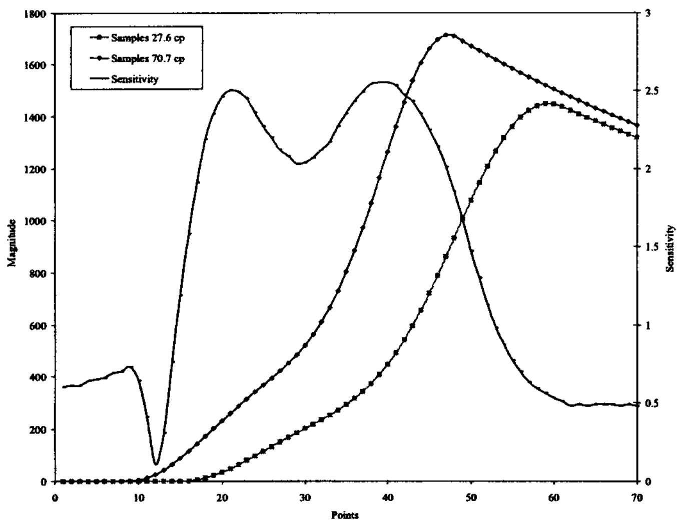

Fig. 9 – Sensitivy of the neural network and raw NMR data for the analysis with the cumulative T2 distribution of the study field viscosity data.