PREDICTING FLUID TYPES FROM WELL LOGS USING FUZZY KOHONEN NEURAL NETWORKS

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ABSTRACT: After drilling a well, the identification of zones potentially producing hydrocarbons, depends on the existence of enough geologic and petrophysical information that diminishes the degree of uncertainty to the moment to perforating intervals of interest. At the present time in Colombia and through out the world exist old fields with little well logs information available, however they possess high potential of additional reserves. This job is trying to take advantage of the existence of reports of production tests recorded through the well history, that although they don't possess standardized format, they become a source of valuable information to the moment to make decisions. This information together with data of well logs is used to identify patterns of fluid types that exists in different layers that conform the reservoir using Fuzzy Kohonnen Neural Networks. The first part contains an explanation on the data used in the pattern recognition; the following section shows the model designed with DataEngine™ and finally a well example is presented where the degree of accuracy is observed in the prediction.

DATA SOURCE FOR PATTERN RECOGNITION

The first step required identifying the types of data to be selected during the investigation development, requires knowing the Art State of the traditional processes used in petrophysical analysis to identify zones producing hydrocarbons. Subsequently, to take advantage of new techniques of intelligent data analysis in this analysis types.

Through the time, identification techniques of zones producers and petrophysical properties of the formations of interest have been using empirically and mathematical models defined for the system conditions.

By means of revision of information sources corresponding to the Petrólea Field, were retrieved production history files for 220 wells. The other information source, the well logs, requires to identify the common curves for all wells to be processed. It was developed a model to classify just only three curves related with petrophysical behavior, e.g. Spontaneous Potential (SP), Short Resistivity (SR) and Long Resistivity (LR). Those curves were found on sixty wells. The SP curve is used for Shally/Clay or Sand zones identification, the SR and LR curves are used to identify fluid types in washed zones and virgin zones respectively. The washed zone is located near borehole and is formed during drilling process where drilling fluids, called mud, invade little meters the formations.

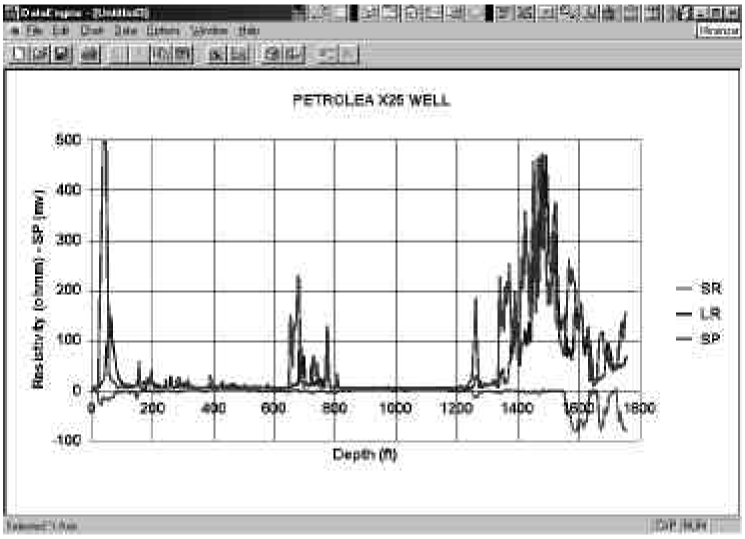
The production history per well was recorded for different operators. The format is not unified and the words used to define production test results are ambiguous e.g. there is not a unique depth interval isolated during production test, there would be two or three or more. The operator would be ignoring stimulation jobs. So during training and labeling process it was needed to select short intervals where the terms have a minimum vagueness.

On the other hand the linguistic terms defined for fluid type identification are as follows:

Dry (D): there is nothing, without fluid.
Water (W): the main fluid present is water.
Oil (O): It is referred to every kind of hydrocarbon e.g. oil or gas. However the concept of experts on Petrolea Field are sure there is not gas in the reservoir.
Stimulation (S): This linguistic term is related with zones needing external help to flow. The lithology is mainly calcareous on Petrolea field and the reservoirs are naturally micro fractured. The most of production test reports shown that it was needed to inject HCL acid and to wait for well production, after 3 up 24 hours the well flows although not always.

The normal behavior of SP, SR and LR for Petrolea X25 well is depicted in Figure 1. Intervals with higher resistivities apparently have hydrocarbons and lower have water, however FKNN shown different results.

Figure 1. Curves behavior on Petrólea X25 well



PRE PROCESSING INPUT DATA ATRIBUTES

The data attributes pre-processing include the following steps:

- To establish format conversion from Log Ascii, LAS 2.0, to DataEngine ASCII file. There was developed a external library for this purpose.
- Determining statistical parameters such as maximum, minimum, media, variance, standard deviation, range, Kurtosis and Skewness factors and null intervals
- Three log curves selected were not run for all well depth, so it was needed to eliminate zones without full information.
- The LAS 2.0 original files were old files. Those files were digitized (converted from graphical format to digital format.) using different tools with lower precision. So it was needed to edit wrong values using expert knowledge.
- It was implemented an external module for automatic identification of fluids reported on well production history through all depth.
- Data attributes standarizing and normalizing.

Figure 2. SR Attribute before standarization and normalization

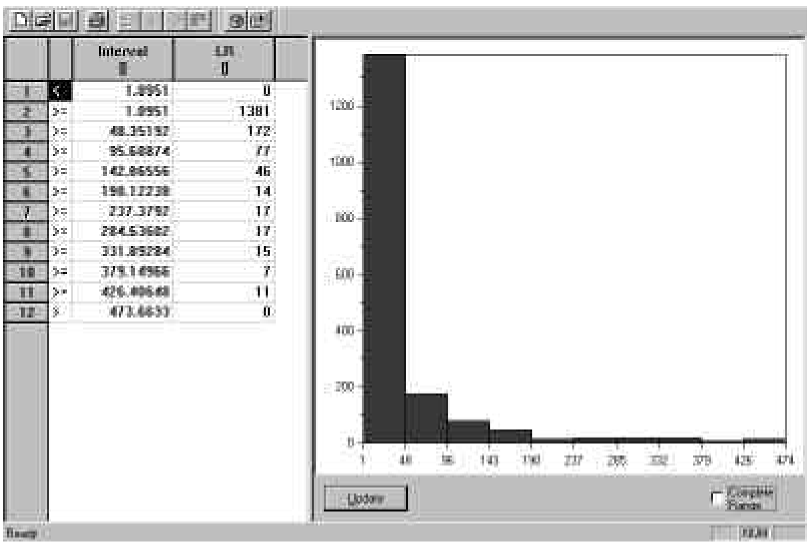
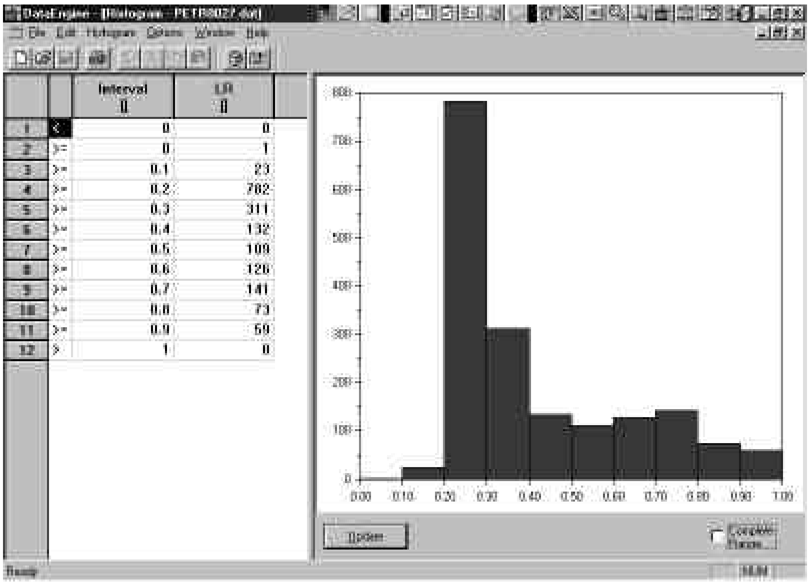


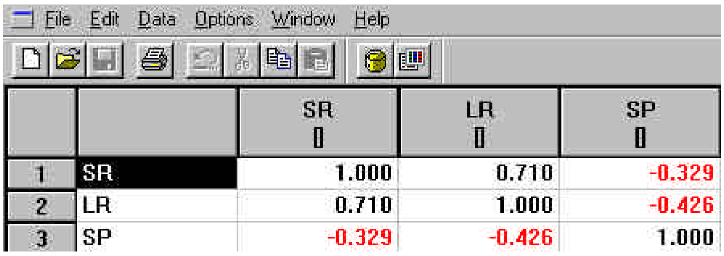
Fig. 3 LR attribute after standarization and normalization.



		Interval	LR
1	<	0	0
2	>=	0	1
3	>=	0.1	23
4	>=	0.2	782
5	>=	0.3	311
6	>=	0.4	132
7	>=	0.5	109
8	>=	0.6	126
9	>=	0.7	141
10	>=	0.8	73
11	>=	0.9	59
12	>	1	0

Besides Bravais-Pearson correlation factor for SR and LR is near 1 e.g. 0.71, both attributes are needed during fluid type pattern recognition because SR and LR are needed to identify lithology changes. The Figure 4 shows the correlation factors for three attributes SP, SR and LR.

Figure 4. B&P factor correlation for SP, SR and LR



		SR	LR	SP
1	SR	1.000	0.710	-0.329
2	LR	0.710	1.000	-0.426
3	SP	-0.329	-0.426	1.000

FUZZY KOHONEN NEURAL NETWORK MODEL

For the identification process of fluid types a Fuzzy Kohonen Neural Network (FKNN) is designed, with three (3) layers with fourteen (14) neurons each one, this FKNN architecture is feed by SP, SR and LR.
The elements of the weight vector are initialized in random way among zero (0) and one (1), the fuzzy exponent is started with a fixed value, 3; the exponent step is set at 0.2 and the convergence threshold is set at 1E-005.
During training and labeling processes there were used near 2592 data with minimum uncertainty. The learning is achieved after eighty-two (82) cycles with errors of training and test of zero (0)

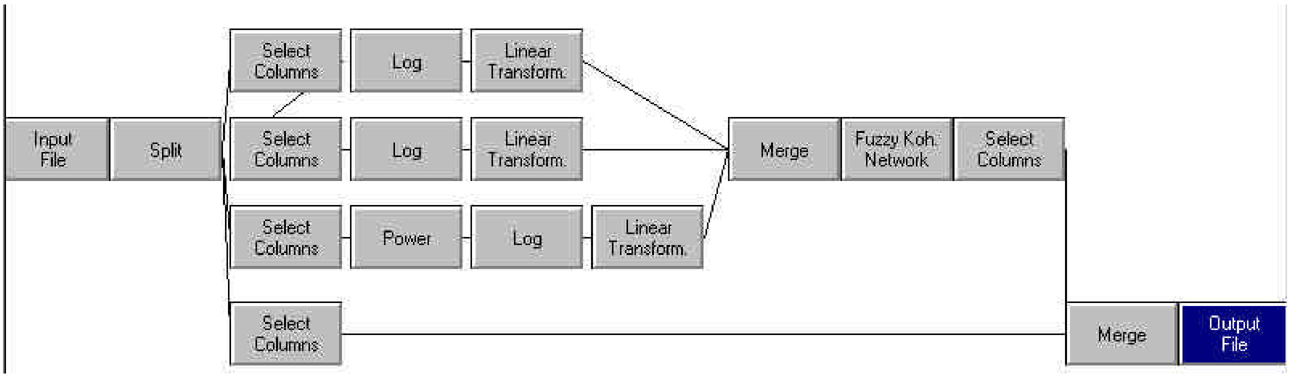
Next section shows the results obtained using the FKNN model.

RESULTS OF FKNN MODEL

Using the language graphic macro is generated an entrance system, processing and exit of attributes for each one of the wells to analyze. The Figure 5, Card of data processing, defines the analysis outline for each well.

In the outline of the Figure 5, it's defined the input for each well that possesses attributes of Depth, Short Resistivity, Long Resistivity and Spontaneous Potential. It's applied the logarithm or power function with the purpose of standardizing resistivities and SP, and later those are transformed linearly for normalizing purposes. Subsequently the fluid type FKNN model is used and the output results are saved in a file per each well.

Figure 5. FKNN model for predicting fluid types on Petrólea Field



The FKNN model was used for sixty wells with accuracy between 90 and 95% compared with production reports. The Petrólea 37 well is used as an example. The figure 6 depicted the behavior through all well depth. Most of zones are dry however there are some intervals like as 800 to 900 ft, 1000 to 1150 ft. and 1400 to 1480 ft. where it seems to be any type of fluids. The Figure 7 shows the interval between 1400 to 1480 ft. the production history reported dry hole, we have found with FKNN model a zone which will be producing hydrocarbons but requires acid stimulation to flow. The zones are dry and won't flow unless be stimulated.

Figure 6. Identifying fluid types on Petrólea X25 well

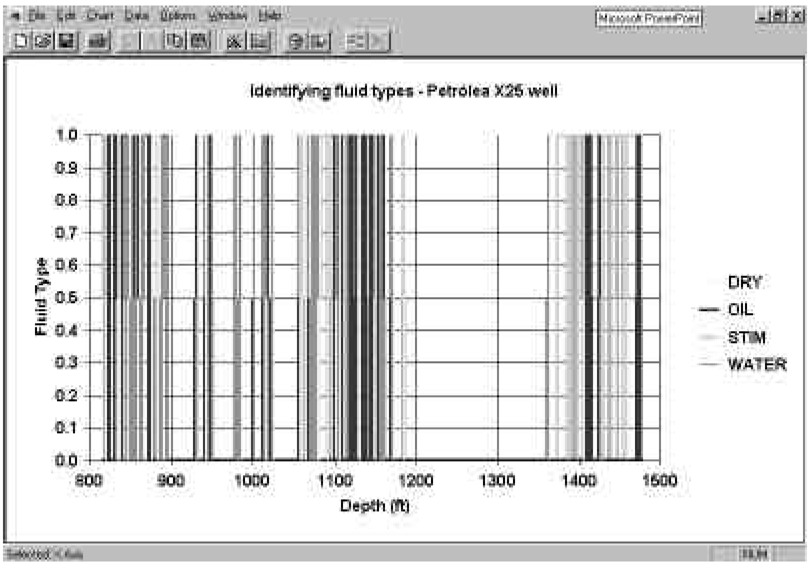
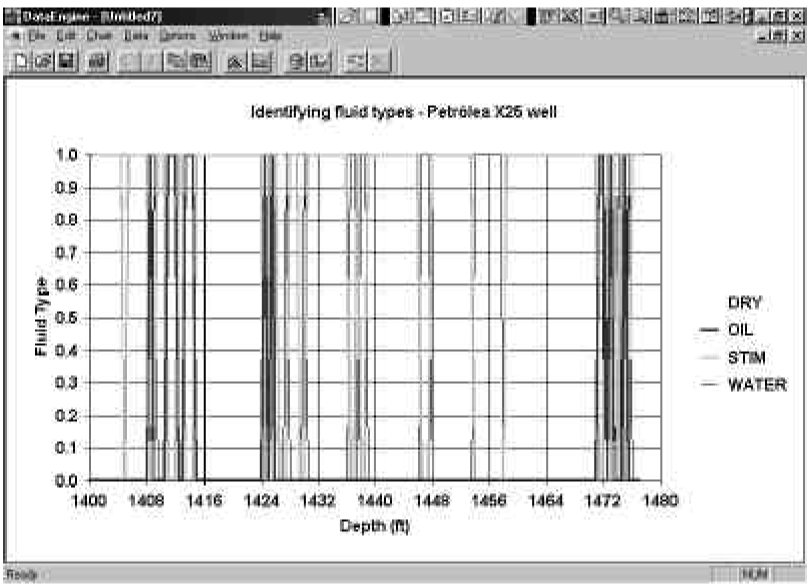


Figure 7. Identifying fluid types - Interval Petrólea X25 well



CONCLUSIONS

It's demonstrated that DataEngine™ using Intelligent data analysis techniques improved the results obtained in fluid types prediction, compared with traditional interpretation methods. The results found with this brand new method were between 90% and 95% compared with production history information. Meanwhile traditional petrophysical analysis method besides was too complex, found accuracy between 80% and 90%.

There are several software modules that would be integrated with DataEngine™. Those modules such as LAS format conversion, intervals handling, graphical reports and others should be commercialized to Petroleum Industry.

REFERENCES

MIT GmbH 1995, DATENGINE – Data Mining by Intelligent Data Analysis. Part I – Basics. Part II - Tutorial. Addendum. Aachen, Germany.