Well Log Estimation Using Genetic Algorithms in a case study, Venezuela.

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Resumen

Disponer de un set completo de registros de pozo es de fundamental importancia para la caracterización de un yacimiento. Sin embargo, esto no siempre es posible y se hace necesario recurrir a técnicas de estimación de los registros de pozo faltantes. El método de estimación utilizado en el presente estudio representa el registro a ser estimado en función de los registros existentes utilizando series polinómicas. Un algoritmo genético es usado para optimizar los coeficientes de las series polinómicas. Este modelo no lineal es entrenado en una localidad donde todos los registros de pozo están presentes, y luego, el modelo entrenado es utilizado en una localidad con un registro faltante (registro objetivo).

En el presente estudio se utilizó el método descrito para estimar registros faltantes en un área del Lago de Maracaibo en Venezuela. Se obtuvieron un total de nueve (de nueve) estimaciones satisfactorias de porosidad, y cinco (de siete) estimaciones satisfactorias de registros sónicos.

Summary

Having a complete set of well logs is crucial for reservoir characterization. Since this is not always the case, it becomes necessary to resort to some technique for estimating the missing logs. The estimation method being applied here uses a polynomial series that represents the target log as a function of other well logs present. A genetic algorithm optimizes the coefficients of this polynomial series. The non-linear model is trained at a location where all the well logs are present, and then, the model is taken to a location with a missing log (target log).

We used this method to estimate missing well logs in an area of Lake Maracaibo, Venezuela. We obtained nine out of nine satisfactory estimations of porosity logs and 5 out of 7 satisfactory estimations of sonic logs.

Introduction

Genetic Algorithms have found many applications within the various disciplines related to the petroleum industry. The advantages they offer as an optimization technique are that they can solve large and complex problems, and deal very well with nonlinearity. They have been used to solve exploration and production engineering problems like material balance, and multiple suppression in seismic data (McCormack, M. et al., 1999). Other uses include inversion of seismic data (Boschetti, F. et al., 1996), petrophysical property estimations (Jimenez and Michelena, 2000) and even product scheduling at coalmines, or pipeline product routing (McCormack, M. et al., 1999).

Banchs et al. (2001) have proposed a non-linear method for estimating missing logs, which is based on genetic algorithms. The method consists of computing a non-linear model, which expresses a target or missing log as a function of other existing logs in the form of polynomial series. A genetic algorithm is used to optimize the coefficients of the series. This non-linear model is trained at a well that contains a complete set of logs. In this first step, a synthetic target log is computed and compared with the existing one at the well. Then, in a second step, the trained model is used along with the corresponding logs at the new location to make an estimation of the missing log.

The Estimation Procedure

The devised procedure for estimating missing logs consisted of three steps: data gathering, preliminary testing and actual estimation. In the first step, all the available information for the area of interest is gathered and studied. In the preliminary testing, some tests are made to asses the quality of the estimations being done. Finally, the actual estimation is made.

The information to be gathered includes geologic correlation between wells (which is absolutely necessary for a successful estimation), a list of all available logs, depth intervals in which the logs were taken, intervals for null values and preferably a visual display of the logs at the depth intervals of interest. Once all this information is collected, it is studied to determine the compatibility of the training and target sites. The restrictions on compatibility are: the target site must contain all the logs that will be used in the training site with the exception of the missing log, there must exist geologic correlation between the training and target wells, the logs must be measured with the same step, and there cannot be any null values within the depth intervals to be trained and estimated.

There is also a restriction for the length of the trained and estimated intervals, since variations in depth of the petrophysical properties make more difficult the process of training the polynomial series. Therefore, the optimal depth range for estimation must be determined by the characteristics of the area.

Well Log Estimation

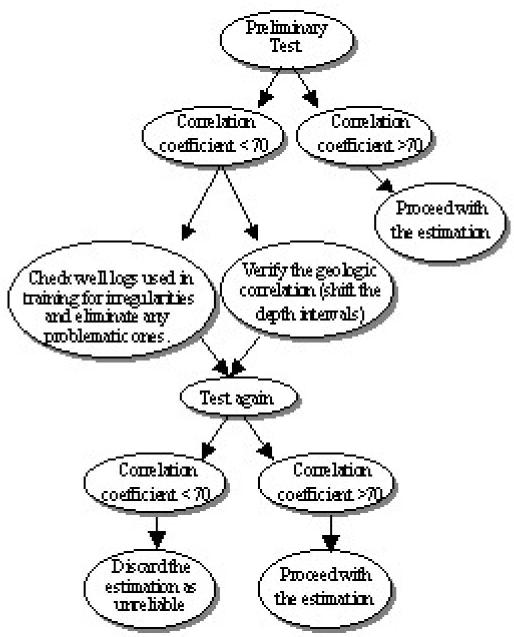

Figure 1: Procedure for the Estimation

Figure 1 shows the procedure to be followed for the estimation. Once the data gathering is carried out, it is convenient to execute some preliminary tests to verify the quality of the estimation.

These tests are performed using the logs that will be used in the training of the actual estimation. The target log for the test should be one that is present in both wells, this way there will be a correlation coefficient at both the training well and the target well. If both coefficients are satisfactory (greater than 0.70) then the actual estimation is carried out. If there is a problem with the correlation at the target well, then adjustments must be made to the planned routine until either the problem is solved or the estimation is discarded as unreliable. The typical problems are geological correlation between wells and unreliable logs.

There is still no way to measure the uncertainty of the actual estimation, but preliminary testing will provide an idea of the method's reliability for the area of study.

Results

In this section we present the results of a study in which we estimated 1000 feet of porosity logs at nine wells and sonic logs at seven wells, each one broken up in intervals of 200 feet. The area considered in this study has a low angle dipping structure so that most of the training and target wells had to be correlated geologically at different depths.

Some modifications to the original data gathering were necessary due to defective logs that had to be discarded from the training, and to inaccuracies in the geological correlation between the wells.

Table 1 presents a sample of a result obtained from the estimation of a porosity log. All the results shown (rows 1-6) correspond to training at a well A and estimating at a well B, where geologic correlation determined that both the training and estimation depth intervals were the same. These results are from a single 200 feet depth interval.

The logs used in the training for the estimation were: density (RHOB), spontaneous potential (SP), medium induction (ILM) and gamma ray (GR). As a preliminary test we estimated the gamma ray log present in both wells. The first two preliminary tests (rows 1 and 2) had unsatisfactory results because the correlation coefficients for the estimation at the target well were below 0.70. After checking the printed logs for the depth interval at the target well we observed that the spontaneous potential (SP) presented an unreasonable behavior. Therefore, we discarded the SP log and included the caliper log (CALI) for training and tested again. The third and fourth results show a high correlation coefficient for the estimation, so the actual estimation of the porosity log (NPHI) was carried out. The correlation coefficient at the training site for the porosity log is comparable to that of the preliminary tests, so we assume that the estimated porosity log is reliable.

	Training logs	**Estimated logs**	**Training Correlation Coefficient**	**Estimation Correlation Coefficient**
1	RHOB/SP/ILM	GR	0.86	0.21
2	RHOB/SP/ILM	GR	0.85	0.31
3	RHOB/CALI/ILM	GR	0.86	0.87
4	RHOB/CALI/ILM	GR	0.86	0.86
5	RHOB/CALI/ILM/GR	NPHI	0.86	
6	RHOB/CALI/ILM/GR	NPHI	0.85	

Table 1: Results Obtained From the Estimation of a Porosity Log.

In a similar manner, the other 800 feet of this porosity log were estimated, as well as another eight porosity logs and seven sonic logs at other well locations in the area. Different training wells were used on some of the other estimations. In all the porosity logs estimated, the correlation coefficient at the training site remained above 0.69 and many were above 0.9. Five out of the seven estimated sonic logs were considered satisfactory. Most had correlations at the training site greater than 0.75, but the reliability of these estimations were regarded as more dubious due to the differences (ranging from 0.02 to 0.2) between the correlation coefficients. Estimation of missing spontaneous potential logs was attempted, but the poor quality of the existing SP logs rendered the training ineffective, and most of the correlations remained under 0.2.

Conclusions

The non-linear method used for estimating missing well logs has proven to be effective. We accomplished nine successful estimations of porosity logs and five out of seven successful estimations of sonic logs in the area of study. Although we still have no way to quantify the uncertainty of the estimates, the correlation coefficients allow us to get an idea of their reliability.

The main limitations on the method are the quality of the logs used in the training and estimation processes and the accuracy of the geologic correlation between wells.

References

Banchs R., Jiménez J., Del Pino E., "Non Linear Estimation of Missing Logs from Existing Well Log Data", S.E.G, San Antonio, TX, 2001

Boschetti, Fabio., Dentith, Mike C., List, Ron D. "Inversion of seismic refraction data using genetic algorithms" Geophysics, Vol. 61, No. 6 (Nov-Dec 1996); P. 1715–1727

Jiménez J., Michelena R., "Estimación Rápida de Propiedades Petrofísicas Usando Múltiples Atributos Ortogonales y Algoritmos Genéticos", X Congreso Venezolano de Geofísica 2000

McCormack, M., Stoisits, R., Macallister, D., Crawford, K. "Applications of genetic algorithms in exploration and production" The Leading Edge, June 1999 P.716-718