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Fluid Substitution Using Pseudo-Sonic Logs Generated by Neural Networks: A Modeling Study

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Abstract

There are many steps in a 4-D feasibility study before reaching a final conclusion. One of the most important steps is the prediction of the impedance and velocity variations due to changes in reservoir conditions(pore fluid saturation, pressure, temperature), using Biot's theory to make a fluid substitution. When dealing with old wells with a "limited' logs suites the lack of shear wave velocity logs(VS) is a very common situation, a problem arises when there are no compressional wave velocity logs(VP) available, or VP data is not reliable. There are many methods of generating VS from VP data, and the applications of the knowledge of VS are many for example: borehole stability and DHI analysis. We chose 8 wells of Brazilian offshore reservoir covering an area of 60 km2 of extent and simulated a fluid substitution study using sonic logs generated by artificial neural networks and compared the impedance changes predicted by them to the impedance changes predicted by the fluid substitution applied to the original curves. The pseudo-sonic well logs match very well the original ones for all the wells and the core velocity measurements available. The core measurements were used first to calibrate and validate the training well and then, for evaluating the quality of pseudo-sonic logs. The porosity and density logs were used as input curves for the artificial neural networks. The examples presented in this paper shows that a fluid substitution study can be carried out on pseudo-sonic logs generated by neural networks using density and porosity logs, although they do point out some critical points like geographic extent of training data, amount of input parameters, etc. The particular features of each reservoir must be evaluated and analyzed before trying to apply neural networks as a log generator for a 4-D project, in this sense laboratory velocity measurements in cores are one of the most important data in evaluation and calibration of the sonic, logs before fluid substitution and after that, in order to evaluate the pseudo-sonic logs.

INTRODUCTION

The production of oil or gas, and fluid injection on EOR process causes changes in seismic properties of a reservoir. The repeatability of 3-d surveys is very useful tool for mapping the pore fluids distribution, pressure fronts, temperature variations, etc. This kind of survey, known as 4-D seismology or Time-lapse Seismic Reservoir Management(TLSRM), is a high-cost survey, that's why it is necessary a previous analysis concerning to the properties of the reservoir. The main purpose of 4-D feasibility analysis is to answer the following question: Will this new 3-D survey be able to see the differences in seismic attributes caused by production and recovery process?

The feasibility study is one of the most importants steps in a 4-D project, this study through a careful well log analyses and calibration intends to predict the seismic response, in terms of velocity and impedance variations, to the changes(since the last survey) in reservoir internal conditions, like fluid saturation, temperature and pressure. The compressional(VP) and shear(VS) wave velocity measurements in cores with a well log analyses is a very important task in order to validate the VP curves, Dillon et al.(1998) shows an interesting case of a VP curve correction using core velocity measurements and its impact on seismic modeling of 4-D feasibility project. There are many methods of generating VS logs from Vp ones, but it is necessary to have a reliable VP data. It is a very important point, since the applicability of VS data are many, ranging from borehole stability to DHI analysis and AVO modeling.

After the VP curves validation, the next step is to try to generate the sonic response to the predicted changes in pore fluids, temperature and pressure due to production and/or a recovery process, it is the so-called "fluid substitution", that uses Biot-Gassmann(1956) equation. The original VP curve, representing the original fluid, and the new one will both serve as input curves to seismic modeling, where the estimated impedance and velocity changes will be greater than the differences obtained from well log modeling. Impedance changes greater than 4% are supposed to be detected by seismic method.

If there is a complete log suite available the analysis is easier and more accurate, but if one needs to work with old wells the situation is much more complicate. A problem arises when there is no VP curve available, the VP data are not satisfactory or sparse. Therefore we decided to simulate a fluid substitution analysis using pseudo-VP logs generated by an artificial neural networks(ANN), which is a general purpose tool, in order to compare the conclusions from the simulation with original curves to the conclusions from pseudo-logs, supposing there was only a "limited" suite of logs for the group of wells.

ARTIFICIAL NEURAL NETWORKS

Artificial Neural Networks (ANN) are computational techniques whose algorithms try to simulate the inner working of the human brain using models based on the synapses of neurons. ANN has been successfully applied to many fields as they can handle complex, non-linear problems quickly and easily, simplifying the make of new decisions, classifications and predictions.

The main feature of ANN is that they are trained by examples and thereby are able to learn to recognize patterns. This characteristic in addition to the fact that even in a situation where there is a limited data available they can build a high-quality solution make them a good option for those who work with well logs.

The backpropagation neural network has become the most widely used tool in the field of ANN. Basically it consists of one input layer, one or more hidden layers and an output layer. Figure 1 shows a schematic diagram of a backpropagation neural network with two inputs, two hidden layers and one output. It is a two step algorithm. Initially the input information flows through the net, crossing the hidden layers producing an output. This output is compared to the desired output, and an error is computed. The error is then backpropagated from output layer to each element in the hidden layer. Each element of the hidden layer receives only a portion of the total error, proportional to its contribution. Based on the error received, connection weights are then updated by each element to cause the network to converge toward the desired output. For some applications of ANN see Schmidt (1992) and Lorenzeti(1992).

METHODOLOGY

Eight wells from a Brazilian offshore reservoir, covering an area of about 60 km2 of area were selected. The wells depict a turbidite sandstone locally cemented by calcite with thin layers of shales and diamictites.

We separated this group of wells into two sub-groups, group 1 with three wells: one chosen for training the network (training well) and the others for testing(confirmation wells); group two with five wells where the trained network was applied. The ANN used in this work was made of one input layer, with two elements, one hidden layer with fifteen elements and an output layer with one element. The training well depicts all lithologies types drilled by the other wells. We selected a minimum log suite available for all logs in order to choose the input curves for pseudo-VP logs generation. As one of our first assumptions was that we were working with a very limited suite of well logs, we tried to use the lowest amount of curves that may provide us reasonable results and conclusions.

Porosity and Density logs were chosen to be used as input curves for training the ANN, because they were available for all the wells and had a good quality. Resistivity curves were used in the beginning but the results achieved with and without this curves were almost the same.

After a synthetic well logs generation using ANN, they were compared to both, the original well logs and core velocity measurements, and then a fluid substitution modeling was carried out on the original logs and synthetic ones. Since Biot's theory gives better results for sandstone, we decide to make the fluid substitution only in the sandstones depth intervals. The original pore fluid, a 27 API oil with water saturation(SW) ranging from 22% to 28%, was replaced by a fluid with SW ranging from 30% to 100%. The impedance variations(IV) estimated for entire range of SW for original(orig) and synthetic(synth) logs were compared and a curve of (IVsynth-IVorig)X Depth was created for all values of SW for each couple of logs. Since there were no shear wave velocity logs, they were generated from VP logs using a linear relation proposed by Dillon et al.(in a PETROBRAS internal report), after more than a hundred of core velocity measurements in laboratory.

RESULTS

Figures 2A and 2B show on their left side, the original and the synthetic sonic logs obtained for the respective wells and the core velocity measurements available. The two wells show a good agreement between laboratory and synthetic data. We also observe an excellent match between the original and the synthetic sonic log, generated by neural network (ANN) for all lithologies in well A . Well B shows a good match for sand intervals, however for the carbonate interval the outcome doesn't show the same quality as observed in well A . Nevertheless, the use of the synthetic log would be a good approximation where there is a lack of sonic log.

We simulated a fluid substitution just for the sand intervals. As our aim is to compare the predictions of impedance variation from a fluid substitution using field logs and pseudo-logs, figures 2A and 2B shows in their right side the difference between these predictions. This curve is always close to zero, indicating a good match between the two predictions for fluid substitution when using the original sonic-log and the prediction obtained for the NN-generated data.

CONCLUSIONS

In this work we showed that the impedance variations estimated from a fluid substitution modeling carried out on pseudo-sonic logs generated by ANN can be very close to that ones carried out on the original well logs, leading to a similar prediction on seismic modeling. The areal extent of ANN applicability it is a very difficult question. A very effective way of evaluating the synthetic well logs are the core velocity measurements, the more core measurements available the more confident one can be about the quality of synthetic data. The knowledge of reservoir geology and the expected response of well logs to different conditions of reservoir are very useful for evaluating and mapping the zones where the ANN can be used or not.

Concerning the applicability of VS data, it is very important to have reliable VP sonic data, in this sense well logs calibration must be done every time it is possible or seems to be necessary.

The choice of input data depends on both, characteristics of the reservoir itself and the quality of data available.

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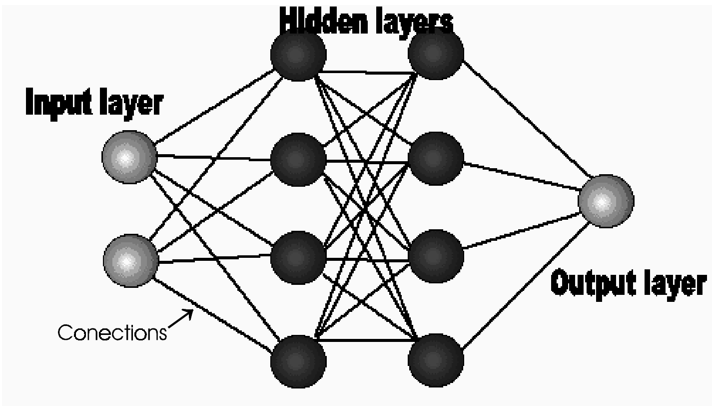

Fig. 1- Schematic diagram of a Backpropagation neural network

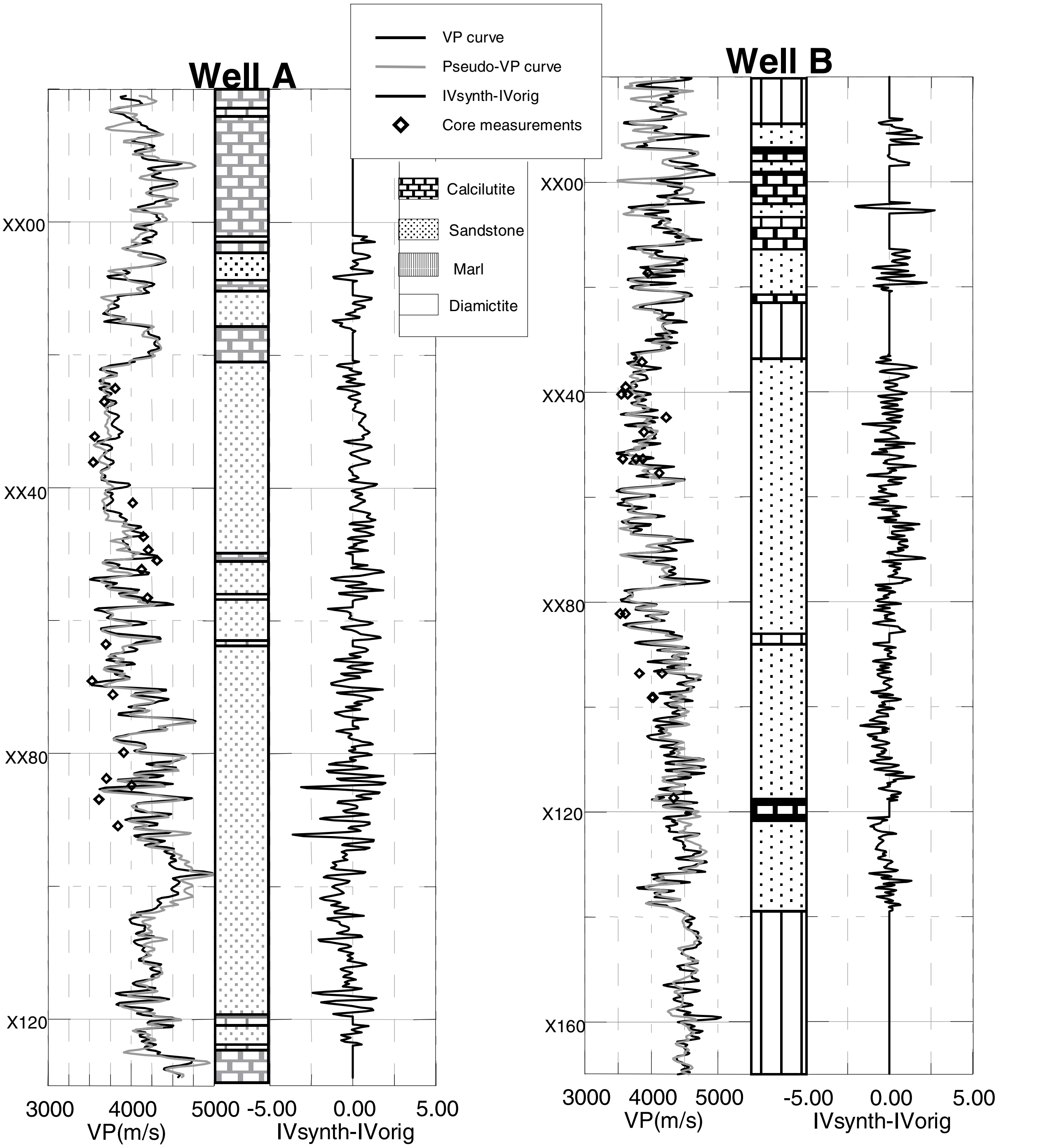

Fig. 2A - left: Original and synthetic VP
right: Prediction difference in a fluid substitution simulation(oil to water) between original and synthetic

Fig. 2B - left: Original and synthetic VP
right: Prediction difference in a fluid substitution simulation(oil to water) between original and synthetic