GeoConvention 2015
GEOSCIENCE
new horizons
Telus Convention Centre • 4-8 May 2015 • Calgary, AB Canada

Quantitative Analysis Workflow to Correlate Seismic Attributes and Production Data in Horizontal Wells

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Summary

We present a quantitative analysis workflow to find relationships between seismic attributes and production data of horizontal wells, with the ultimate goal of mapping production potential of unconventional shale and tight-sand plays using seismic attributes before drilling. The workflow consists of four steps: 1) extracting seismic attributes in the near wellbore volume of prodution zones; 2) multivariate correlation analysis of production data with the near-wellbore seismic attributes, drilling and completion parameters; 3) neural network training between production data, drilling and completion parameters; 4) mapping production potential from the trained neural nework using seismic attributes as the input. The above workflow is illustrated using a synthetic data set which has the "ground-truth" and thereby allows for sensitivity analysis of input parameters to the predicted production volumes.

Introduction

Production from fracked horizontal wells in shale and tight-sand plays are notoriously variable, not only betweeen wells, but also between fracking stages in the same well. It has been reported that the production can still change a lot for the same completion and drilling processes (). Geologically, it is reasonabel to expect that the rock properties along or near the well path will have the fundmental control on the production volume of a horizontal wells. There are numerous rock properties that have been proposed as the influencing factors to the horizontal production (Table 1), in addition to a large set of drilling and completion parameters (Table 2). Optimization of drilling and completion parameters are certainly critical in realzing the production potential at well locations.

3-D seismic technology have played critical roles in the conventional exploration and production. They have been used to map, delineate and characterize structures and stratigraphic seals and reservoir properties, leading to more discoveries with reduced risks. A similar objective should be achievable for unconventional shale and tight-sand plays. This is the ultimate goal of the workflow described in this paper. In the next section, we will first describe assumptions and theory in the development of the workflow. Each step of the workflow is then outlined. We'll use a synthetic data set to illustrate the whole workflow.

Theory and Workflow

There are two types of reservoir properties that impact horizontal well productions. The first type are those related to the amount of oil and gas in place, such as reservoir thickness, porosity, total organic matter (TOC), and thermal maturity. The second type of parameters are those that relate to the efficiency of fracking and the connectivity created in the fracking, such as mineral composition, rock mechanical properties, local stress orientation, fracture density and orientation. Pre-stack seismic inversion methods have been developed to invert some of these parameters (), and a "fractability map" can be derived to guide the pre-drilling decisions. This is a model-driven workflow, where physical models are assumed in both seismic inversion, as well as in the interpretation of these inverted properties to the fracking processes. A data-driven workflow could also be developed to map the "sweet-spot" in unconventional players, because multi-year production data are now available in the major shale and tight sand plays of North-America. In the following we outline the data-driven workflow that we developed. We don't assume any priori models between fracking efficiency, production, and seismic attributes, but rely on the production data and seismic attributes extracted from near-wellbore volumes in a training area. The multivariate statistical analysis and article neural network are the methods used to detect the relationship between production and the seismic attribute in the near wellbore volumes. Drilling and completing parameters are also used during the analysis, to quantify the relative impacts of each group of parameters to the production volume. The relationship derived from data-driven method can also be used to locate "sweet-spots", where the geological setting are similar to the training data area.

The quantitative analysis workflow of correlating production data and seismic attributes consists of four steps:

Step 1: Extracting seismic attributes within a near-wellbore volume (NWV) of horizontal well. All types of seismic attribute calculated from post-stack amplitude or inverted from pre-stack inversion can be used as the input. A near-wellbore volume must be defined in the production interval. The simplest form of near-wellbore volume is defined in the horizontal direction by a radius perpendicular to the well path, and by top and bottom horizons in the vertical direction. We used the strata-grid concept in the attribute analysis (Wen, 2012) to define the target reservoir zone. Figure 1 shows examples of near wellbore volumes used in the example below. All samples of a seismic attribute in a NWV must be "upscaled" to one value. The upscaling methods can be a simple arithmetic averaging, root-mean-square averaging, harmonic.

Step 2: Multivariate statistical analysis of between a production parameter (e.g., accumulative production volume in the first 6 months), all upscaled attributes in NWV, all drilling and completion parameters to be considered. The analysis methods we used include bi-variant correlation, statistical test, principal component analysis, step-wise regression, and multivariate regression. The end results of this step is to identify a set of seismic attributes that are correlated with the production parameter, as well as the relative contribution factors to the production by seismic attributes set, drilling parameters and completion parameters.

Step 3: Neural network training. The seismic attributes that are found to be correlated to the production data are used as input to train a neural network to predict the production from seismic attributes. The neural network we used in this workflow developed are xx (). Blind well test must be done in this step to validate the trained NN is able to capture the complex relationship between the seismic attributes and the production data.

Step 4: Using the neural network trained in step 3, the production potential maps will be generated in this step from the seismic attributes in the area where drilling locations are to be selected,

Even through the data-driven approach does not use the clear understanding of the physical meaning in each seismic attributes, we assume the spatial variation of reservoir properties will be related to the changes of seismic attributes. The neural network will capture the hidden relationship between the production data and seismic attributes. Since the final data that are used in the multivariate data analysis and neural network training are an upscaled value inside the NW, the quality of correlation and prediction will be dependent not only on the specific attributes, but the size of NV, upscaling method of seismic attributes, and also the type of production data (e.g., accumulated production in the first week, the three months or the first 12 month). Sensitivity of each input and the final results must be carefully examined when applying the trained neural network for predicative application.

Conclusions

The multi-variatle data analysis method, together with neural network, can be used to investigate the relationship between production data and seismic attributes extracted from near-wellbore volumes around horizontal wells. Drilling and completion parameters can also be used in the analysis process. The established relationship in the producting area can be used to apply seismic attributes for selecting better drilling locations and completion parameters.

Acknowledgements

Mohammed Alibrahim and Rongfeng Zhang are gratefully acknowledged for their contributions in the development of the quantative workflow presented in this paper.