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Author **Abhishek Shukla , Emerson Roxar , India**

Co-Authors **Jyoti Rout**

Automated workflow to quantify GRV uncertainty in 3D geological model

Abhishek Shukla[1], Jyoti P. Rout[2]

Roxar Software Solutions, Emerson Innovation Centre, Pune 411057, India,
[1]abhishek.shukla@emerson.com,[2]jyoti.rout@emerson.com,

Summary

GRV uncertainty is often the most significant uncertainty, especially in the early phases of field appraisal and development, and the correct handling of the structure and contacts is often the key to a realistic uncertainty assessment and asset management. Gross rock volume is to a large extent controlled by the structure of the horizons and faults, and the fluid contacts.

This paper deals with handling uncertainties which are present in various elements of structure model and how these can be calculated in an automated workflow to quantify uncertainty in GRV of field. The Model Driven Interpretation functionality in RMS allows the user to specify uncertainty for the interpretations and later the horizon uncertainty modeling used for stochastic depth conversion can take various uncertainty input to create equiprobable realizations and quantify their impact on GRV.

Introduction

The main sources of GRV uncertainty are:
1) Uncertainty in seismic surfaces
2) Uncertainty in Velocity model
2) Uncertainty in interpreted well picks
3) Uncertainty in Fluid contacts

Uncertainty in seismic interpretations can be quantified by model-driven interpretation process in RMS, a standard deviation map is extracted which is used to capture the uncertainty prior to the building of a structural model and is then taken through the remaining elements of the workflow to create multiple realizations.

Uncertainty in the velocity model can be defined by assigning probability distributions to the parameters of the model (Trend, residual). The input parameters can be constants, functions or maps. Velocity uncertainty maps are particularly useful for incorporating realistic lateral variations such as increased uncertainty away from well data and down dip. These maps can be based on well miss ties, analysis of stacking velocities and general experience from nearby fields. An uncertainty model for velocities can be used to generate multiple realizations of the depth structure (Horizons and Faults

One of the main bottlenecks which has prohibited the use of 3D models in uncertainty quantification has been the automated building of consistent structural models. The building of consistent fault and horizon models has generally required significant manual intervention. The 3D modelling workflow requires that the building of the structural models is fully automated even when the input fault and horizon data are changed for each realization.

The modern structural modelling algorithms in Roxar's RMS are fully automated and robust to changing input data. The algorithms allow the fault model and horizon models to be rebuilt automatically to produce multiple realizations the reservoir structure with consistent depth surfaces, isochores and faults. The development of fully automated, robust structural modelling algorithms is one of the keys which facilitate the implementation of the 3D GRV uncertainty modelling workflow.

One of the main benefits of working in 3D is that intrinsic geological dependencies are incorporated in the uncertainty analysis. For example, reservoir gross rock volume (GRV) is primarily controlled by structural depth, reservoir thickness and contacts. Structure and contacts need to be accounted for together. Correct quantification of GRV requires that structure and contacts are modelled together and not treated separately. When uncertainty in the depth conversion is modelled this introduces uncertainty in the spill point depth. This means that the spill point depth can occur anywhere between the Oil-Down-To and the structural spill point, which varies for each realization. The implication of this dependency is that fluid contact distribution becomes skewed with higher probabilities for shallow contacts and a tail towards deeper contact. This distribution is realistic from a geosciences perspective, but is almost impossible to predict without using a 3D model.

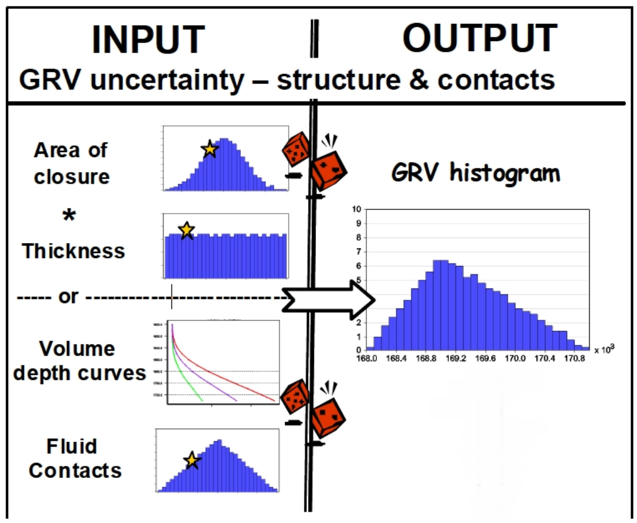

Figure 1: Convectional /Non-3d Workflow for Monte Carlo sampling of the standard GRV uncertainty calculation. Monte Carlo sampling of the input distributions are used to define directly the GRV uncertainty.

Workflow and methodology

First, vertical uncertainty was captured at the interpretation points of all time surfaces. This was done using a method that automatically calculates uncertainty based on seismic data. The methods check for the bandwidth and quality of seismic data at each interpreted point of all reflectors and assign the uncertainty values based on this. Following the model-driven interpretation process, a standard deviation map is then extracted which is then taken through the remaining elements of the workflow to create multiple realizations. After this the uncertainty in average velocity maps at surface each was captured. This was done by generating maps which were based on well miss ties and analysis of stacking velocities.

So, when all the input data required to completely capture the uncertainty in structural model was generated then the data was given to Horizon Uncertainty modelling (HUM) solution in Roxar's RMS.In the HUM the horizons are modeled as a sum of a trend and a residual. The trend captures the large-scale shape of the horizon and the residual captures (small) deviations between the trend and the unknown true horizon. They are adjusted to all used information (well picks, zone logs and changes in the velocity model). HUM requires uncertainty specification for all velocity maps as well as time interpretations (reflection times). Local adjustments around the wells was controlled by the residual uncertainty setting, while global shifts of the entire surfaces to fit the density trend from all well data were controlled by trend uncertainty. In trend uncertainty the uncertainty maps generated above was given for both velocity and interpretations.

The HUM job was simulated for 50 realizations and subsequently the horizon model was created based on Horizon Uncertainty output.

The next stage of the workflow was the creation of a 3D grid. It is through the grid that multiple realizations were generated and eventually Gross Rock Volume ranges (see figure 9). This generates the P10, P50 and P90 GRV values as well as indicating which horizons, velocity models or fluid contacts are affecting the GRV calculation. They can be used directly to calculate volumetric (2D volumetric), or most typically be used as input to horizon modeling and subsequently grid modeling to calculate p90 P50 and P10 values for GRV. Following is a flow chart for short representation of above workflow.

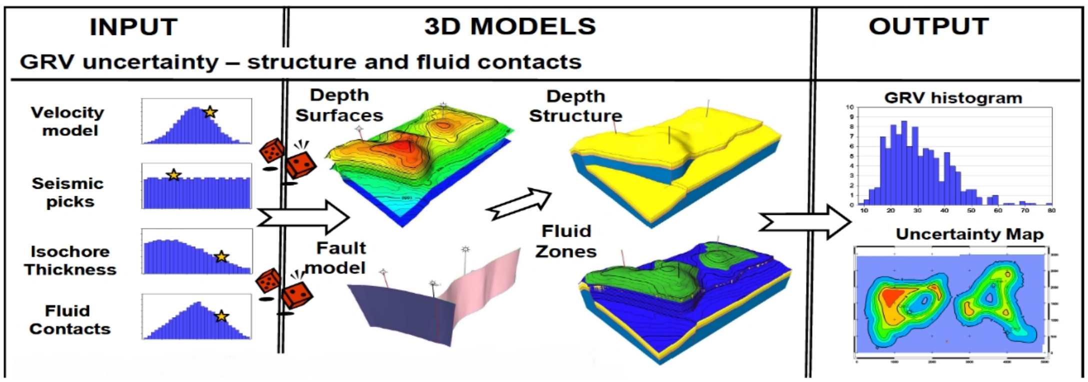

Figure 1: General 3D model based stochastic workflow for GRV uncertainty quantification.

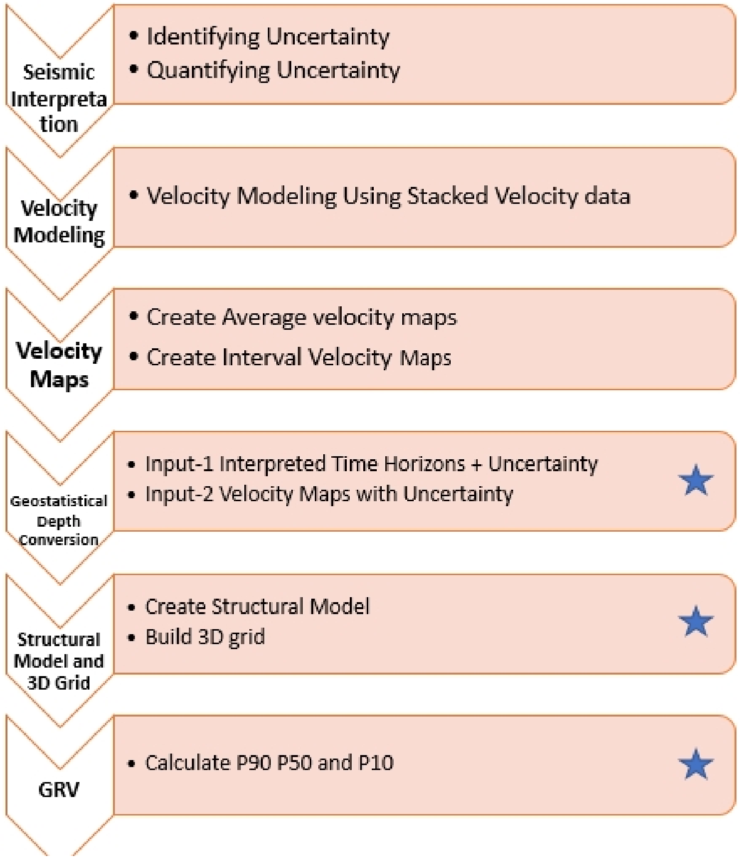

Figure 2: Workflow for 3D model based stochastic GRV uncertainty quantification used in the paper. Star mark indicates multiple equiprobable realizations. Case study using this methodology will be discussed in main paper.

Conclusion

In recent years the quantification, understanding and management of subsurface uncertainties has become increasingly important for oil and gas companies as they strive to optimize reserve portfolios, make better field development decisions and improve day-to-day technical operations such as reservoir characterization and well planning.

The proposed workflow in this paper is fully automated and repeatable. This increases operator confidence in GRV uncertainty calculations through a more complete representation of the seismic data where the uncertainty is guided by the data and where the capturing of uncertainty can take place for each single point during the interpretation process. As compared to the conventional workflow, where uncertainty can only be moved vertically by the constant factor, in the proposed workflow for each point uncertainty is guided by the data.

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