Seismic to Reservoir Simulation: A Cooperative Inversion

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Summary

Cooperative inversion for petroleum reservoir characterization produces an Earth model that fits all available geological, geophysical and reservoir production data to within acceptable error criteria. The mathematical formulation for the inversion requires an appropriate modeling description of both seismic wave propagation and reservoir fluid flow. The inversion requires the minimization of an objective function which is the weighted sum of model misfits for both geophysical and production data. While the complete automation of cooperative inversion may be unrealistic or intractable, geophysical data can provide useful information for enhanced heavy oil production. A methodology is given to demonstrate possible cooperative inversion application in heavy oil reservoirs.

Introduction

The science of reservoir characterization integrates geological, geophysical and reservoir production data in order to optimize petroleum production. Reservoir characterization is becoming increasingly important and is essential for enhancing oil production. Since the world's heavy oil reserves are now estimated to be roughly equivalent to conventional oil reserves, there is an increased focus on reservoir characterization of heavy oil fields.

Cooperative inversion attempts to produce an Earth model whose model response matches all relevant data sets (Lines, Schultz, and Treitel, 1988). The term "cooperative inversion" is used here to include "joint inversion" and "sequential inversion" of data sets. It has been demonstrated that the cooperative inversion of many different data types will reduce the ambiguity of inverting one particular type of data. Therefore, the basic premise of this paper is that the ambiguities of reservoir modeling can be reduced by using all available geological, geophysical, and reservoir production data (figure 1), and that cooperative inversion can produce an improved model. It is also assumed that the estimation of a valid reservoir model will aid in the enhanced oil recovery (EOR). This has been advocated by Gosselin et al. (2003) in a procedure known as HUTS (History matching Using Time-lapse Seismic). The integrated approach strategy should be based on the particular model parameters that honors viscoelastic nature of heavy oils.
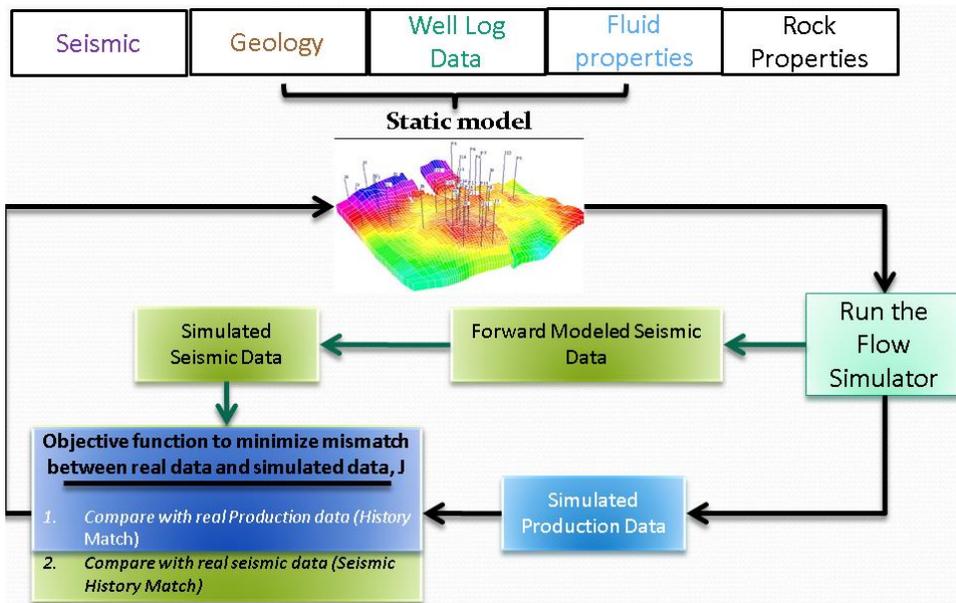
Figure 1. The ambiguities of reservoir modeling can be reduced by using all available geological, geophysical, and reservoir production data in a cooperative inversion procedure.

Theory and Methodology

In order to build a cooperative inversion package as described in the aforementioned papers, one must assemble a set of robust, accurate, (and hopefully fast) modeling codes that describe the geo-data and the reservoir production data. For the seismic data, we will generally use some version of the wave equation which for elastic, isotropic and homogeneous media is given by:

$$(\lambda + \mu)\nabla(\nabla \bullet \vec{u}) + \mu\nabla^2\vec{u} = \rho\frac{\partial^2 \vec{u}}{\partial t^2} \qquad (1)$$

Here $\vec{u}$ is the displacement vector, λ, μ are the Lame' elastic constants and ρ is the rock density. For porous fluid-filled media, one generally needs to go beyond the elastic case to viscoelastic or poroviscoelastic equations (Carcione (2007). The Lame' parameters in case of viscoelastic fluids are frequency and temperature dependent. The condition which rules out the application of either Batzle-Wang or Gassman equation. In our example we employ Cole-Cole correlation and double-porosity elastic medium theories (CPA and Hashin-Shtrikman), to count for frequency and temperature dependence of heavy oils.

Reservoir simulation codes are used to model production history. These codes can be very mathematically complicated, and imbedded somewhere in these codes is some form of Darcy's law. In its simplest form for single-phase fluids in 1-D flow, Darcy's law has the form of:

$$q = \frac{kA}{\eta}\frac{dp}{dx} \qquad (2)$$

Here q is the fluid flow rate, k represents permeability, η is the viscosity, A is the cross-sectional area and the magnitude of the pressure gradient is given by $\frac{dp}{dx}$. Hopefully, both the geo-data and production data have good signal-to-noise levels, and we are aware of the noise (error levels) in our data. In order to produce a valid model whose response agrees with all our data (to within acceptable error levels), we use optimization methods. This is often done by some form of least-squares

optimization which minimizes an objective function that combines the errors in geo-data and production data as in the following equations from Gosselin et al. (2003).

$$\mathbf{J}(m) = \alpha \mathbf{J}_{\text{prod}}(m) + \beta \mathbf{J}_{\text{geo}}(m) \qquad (3a)$$

$$\mathbf{J}_{\text{prod}} = \frac{1}{2}(p(m)-d)^T W_p (p(m)-d) \qquad (3b)$$

$$\mathbf{J}_{\text{geo}} = \frac{1}{2}(s(m)-e)^T W_s (s(m)-e) \qquad (3c)$$

In equation (3a), the model parameters are denoted by m, the production data are denoted by d, the production model response by p(m), the geo-data by e and the geo-data model response by s(m). Here J is the objective function which combines the misfit for the geo-data, s, and the production data, p (Figure 1). The W matrix contains weights for individual data values. The parameters of α and β will weigh the contributions of the geo-data fitting as compared to the fitting of production data. Of course, one of the challenges of cooperative inversion is to determine the weighting factors, α and β. These weighting factors should be related to variance of the errors in our measurements. In fact, if these weighting factors were the reciprocal of the estimated error or "noise" variance, then the objective functions would contain dimensionless norms. The estimation of weighting factors requires that the user have reliable estimates of the "noise" or "error" in our measurements. Hopefully, an accurate model should minimize our objective function.
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Examples

In practice, the numerous uncertain parameters in viscoelastic modeling of elastic moduli should be set to have the best match with real data (Figure 2). Some of these parameters might be measured from the lab measurements, but practically most of them could be set by fitting real data. Figure 2 illustrates the modeled elastic moduli by Hashin-Shtrikman and CPA along with Uvalde heavy oil data (Batzle and Hofmann, 2006). The top table in Figure 2 provides the values for the uncertain parameters which might be set having a measured value, but if not available then we resort to estimating them based on the best fit.

Once all the parameters are set, we can apply them to compute the elastic moduli in every grid of the reservoir model, even if it is optimistic to rely on a lab sample to represent entire reservoir rock. This procedure is similar to a common practice in reservoir engineering history matching, where one trys to tune the equation of state or the relative permeability curves based on limited fluid or core sample and apply the tuned equations to the whole reservoir. In this perspective the uncertain elastic parameters should be used in assessing the match between measured lab data and modelled elastic moduli, or on a bigger scale, between the synthetic seismic model and time-lapse seismic records over the course of production.
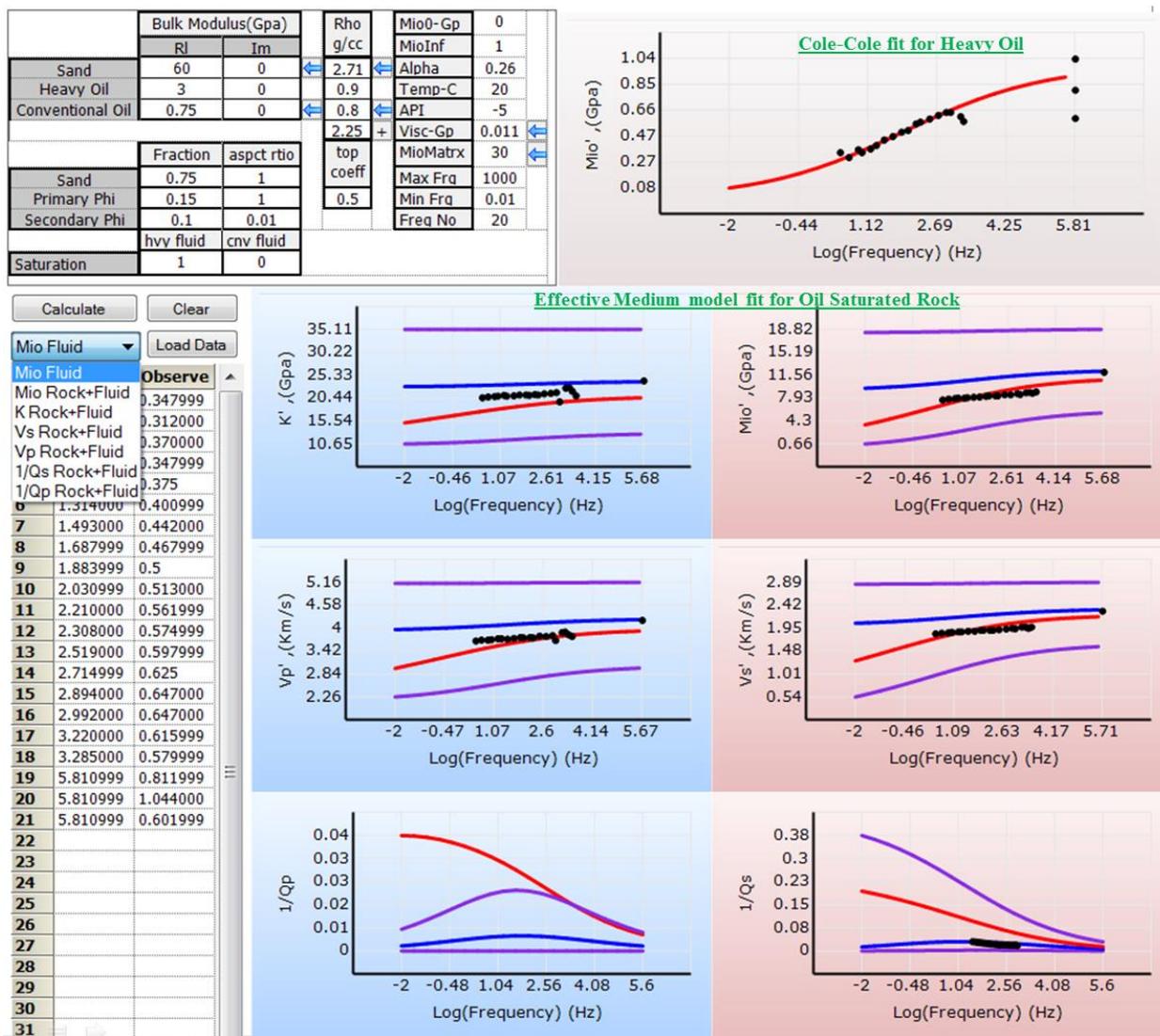
Figure 2. Modeled (lines) elastic moduli along with Uvalde heavy oil data at 20 °C (black dots, from Batzle and Hofmann, 2006), for heavy oil and oil saturated rock. The numerical values of the Uvalde data are shown in the grid cells. The top table shows the modeling parameters. In the modeled elastic moduli for the oil saturated rock, different lines represent the resultant elastic moduli based on different elastic medium methods; upper and lower HS(purple), average HS(blue) and CPA method(red).

Conclusions

Here we defined the model parameters that should be incorporated in the cooperative inversion of the viscoelastic fluids. The forward modeling scheme was shown to be practically beneficial for modeling elastic moduli of the heavy oil saturated rocks and it can be employed to convert simulation data to seismic data

Acknowledgements

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