Mapping of Geomechanical Parameters in Unconventional Shale Reservoir

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Keywords

Geomechanics, Raghavapuram Shale, Brittleness coefficient, Vertical Stress, Pore Pressure, Differential Horizontal Stress Ratio (DHSR)

Summary

Brittleness coefficient and in-situ stress have been estimated from well log data linking post-stack seismic data in the unconventional Raghavapuram Shale reservoir of Krishna-Godavari basin, India. Inverted acoustic impedance, shear impedance, density and compressional to shear wave velocity ratio (Vp/Vs) have been used to train the multilayer feedforward neural network (MLFN) model for mapping pore pressure and vertical stress obtained from well logs. Minimum horizontal stress is computed for anisotropic shale medium. Brittleness coefficient estimated from static Young's modulus and Poisson's ratio is mapped into post-stack section. Fracture index is computed from dipole shear sonic log data. The brittleness coefficient of 20 to 45% and differential horizontal stress ratio (DHSR) of 7-16% with 20-46% fracture index are noticed in the Raghavapuram Shale. This zones exhibit relatively high values of brittleness coefficient and relatively high DHSR.

Introduction

Exploration of Raghavapuram Shale reservoirs depends on the thickness, total organic carbon (TOC) and completion quality (Altamar and Marfurt, 2015). It is known from fracture mechanics that more brittle formation is easier to fracture (Zehnder, 2012). Therefore, brittle zone identification in shale to achieve effective fracturing is becoming focus of present research.

Brittleness coefficient of shale is considered as a key factor indicating the measure of fracture under stress. The principal stress acting vertically is the overburden stress or vertical stress of the rock on top of the reservoir. The maximum and minimum horizontal stresses are computed from estimated vertical stress, pore pressure and fracture studies. Formation brittleness has been derived from the relation between Young's modulus (E) and Poisson's ratio (ν) which is widely used in stimulating shale reservoirs (Gray et al., 2012). Rickman et al. (2008) has quantified brittleness of high grade reservoir with high E and low ν.

Geomechanical properties such as: E, ν and in-situ stress magnitude mapping in the Raghavapuram Shale reservoir in Krishna-Godavari (K-G) basin using 2D post-stack seismic data will aid in estimating brittleness coefficient of rock. The objective of this paper is to estimate E, ν, in-situ stress, pore pressure, brittleness coefficient and DHSR from two wells in the anisotropic Raghavapuram Shale medium.

Theory

The methodology meeting the objectives of the paper is demonstrated through the Figure 1,

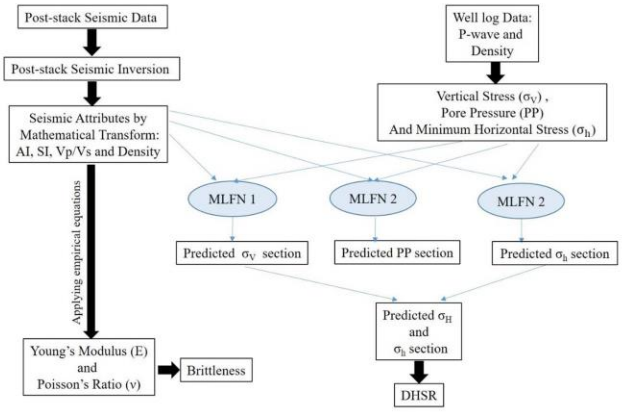

Figure 1: Flowchart showing the steps followed in seismic inversion for estimation of brittleness and development of MLFN models for prediction of vertical stress, PP, minimum horizontal stress and DHSR.

There are relations between Vp/Vs and density (ρ) obtained from well logs and its geomechanical properties (Fjaer et al., 2008).

$$\nu_{dyn} = \frac{Vp^2 - 2Vs^2}{2(Vp^2 - Vs^2)} \quad \text{-----} \ (1)$$

$$E_{dyn} = \frac{\rho Vs^2 (3Vp^2 - 4Vs^2)}{Vp^2 - Vs^2} \quad \text{-----} \ (2)$$

The dynamic E is converted to static E using the correlation proposed by Wang (2000):

$$E_{stat} = 0.4145E_{dyn} - 1.0593 \quad \text{---------------------} \ (3)$$

In general shale gas reservoir is considered as transverse isotropic medium (TI) (Gholami et al., 2015). Young's modulus and Poisson's ratio are having different value in vertical and horizontal direction of shale medium. The values of vertical-E, horizontal-E and vertical-ν, horizontal-ν are obtained from compressional sonic travel time, dipole shear sonic travel time and density logs.

Commonly three mutually perpendicular principal stresses – vertical stress (σ_V), maximum (σ_H) and minimum (σ_h) horizontal stresses exist on the earth crust (Zhang, 2011). For a normal faulting stress regime as in K-G basin the first principal stress is considered to be vertical (σ_V), the second and third principal stresses are σ_H and σ_h respectively (Singha and Chatterjee, 2015). The vertical stress (σ_V) is estimated by cumulative sum of the formation density from the surface to the depth of interest (Plumb et al 1991). Formation density is obtained from density log. Overburden stress or vertical stress can be calculated using the following equation,

$$\sigma_V = \int_0^z \rho(z) g \, dz \quad \text{---------} \ (4)$$

where, z is the depth at point of measurement, ρ(z) is the bulk density of the rock at particular depth and g is the acceleration due to gravity.

PP has been calculated as using Eaton's equation (Eaton, 1972):

$$PP_g = VSG - (VSG - P_{h_g}) \frac{DTCOn^3}{DTCO} \quad \text{--------} \ (5)$$

Where, VSG is the vertical stress gradient, P_{h_g} is the hydrostatic pressure gradient, assumed as 10MPa/km in K-G basin (Chatterjee and Mukhopadhyay, 2002; Chatterjee, 2008 and Chatterjee et al., 2011).

The well penetrated through the Raghavapuram Shale formation shows PP gradient varying from 10.11 – 10.52 MPa/km. The predicted PP is calibrated by the measured pore pressure from Repeat Formation Tester (RFT) data at the selected depths of this well.

Maximum horizontal stress in passive K-G basin had been computed by previous authors and related with vertical stress as (Singha and Chatterjee, 2015, Das and Chatterjee, 2017),

$$\sigma_H = 0.9\sigma_V \quad \text{---------------} \ (6)$$

Minimum horizontal stress considering poroelastic model for isotropic (Equation 7) and anisotropic media (Equation 8) is given by (Gholami et al., 2015)

$$\sigma_h = PP + \frac{\nu (\sigma_V - PP)}{1-\nu} \quad \text{-------} \ (7)$$

$$\sigma_h = \frac{E_{stat_{vertical}}}{E_{stat_{horizontal}}} \frac{\nu_{stat_{vertical}}}{\nu_{stat_{horizontal}}} (\sigma_V - \alpha PP) + \alpha PP + \frac{E_{stat_{vertical}}}{1-\nu_{stat_{horizontal}}{}^2} \varepsilon_h + \frac{E_{stat_{vertical}} \nu_{stat_{horizontal}}}{1-\nu_{stat_{horizontal}}{}^2} \varepsilon_H \quad \text{----------} \ (8)$$

Where, α is Biot's co-efficient and is considered as 1 for K-G basin and subscript "stat" indicates the static property of E and ν in vertical and horizontal direction and ε_h and ε_H are tectonic strain parameters in minimum and maximum horizontal stress direction. Since K-G basin is considered as passive basin (Chatterjee, 2008), the parameters ε_h and ε_H are considered as zero.

Another parameter i.e. differential horizontal stress ratio (DHSR) is very important in determining how a shale reservoir is likely to fracture. The DHSR is computed from maximum and minimum horizontal stresses without any knowledge of the stress state of the shale reservoir. The expression for DHSR is given by,

$$\text{DHSR} = \frac{\sigma_H - \sigma_h}{\sigma_H} \quad \text{-----} \ (9)$$

When the DHSR is large, hydraulic fractures will tend to occur as non-intersecting planes parallel toσ_H. In contrast, when the DHSR is small, fractures induced by hydraulic fracturing will tend to grow in a variety of directions and therefore intersect.

Using the inputs as AI, SI, ρ and Vp/Vs and performing mathematical transform the geomechanical parameters such as dynamic Young's modulus, Poisson's ratio sections have been derived. Neural networks have been used so often for numerical analysis of reservoir properties (Mc. Cormack, 1991; Aminian and Ameri, 2005; Kaydani et al., 2012). The utility of multilayer feedforward neural network (MLFN) models to predict log properties directly from seismic data has been described by Liu and Liu (1998). Here we use MLFN to map in-situ stresses i.e. the vertical stress, minimum horizontal stress and pore pressure (PP) in the study area using the inversion derived attributes using Hampson-Russell software package (Russel and Hampson, 1991).

Three MLFN models are constructed separately for estimation of vertical stress, PP and minimum horizontal stress. For this purpose AI, SI, Vp/Vs and ρ are used as input parameters and vertical stress, PP and minimum horizontal stress are used as target or output for MLFN models. The well W-1 is used as training whereas W-2 well is used as validation well for MLFN models. To initialize the hidden layer weights, average error for trial model is computed by repeating steps for 220 iterations with 4 hidden nodes at the hidden layer. The network is trained with 100% of the available data from well W-1, then validated on log data from well W-2 located 50-60m away from well W-1. The validation dataset is used to avoid over-training or over-fitting through detecting the predicted results in validation group. It is observed that the training error and validation error is reached its global minimum at 100 iterations and then start undulating. Since it becomes minimum at 100 iteration, so the training is optimized with 100 iteration with 4 hidden nodes.

We therefore use vertical stress and PP sections to estimate maximum and minimum horizontal stress section using equations 6, 7 and 8 respectively. DHSR mapping is carried out in the seismic line using derived horizontal stresses from seismic data linking equation (9).

Case Study

N-S oriented post-stack seismic section passing through two vertical wells W-1 and W-2 at 30m and 83m bathymetry respectively is chosen for mapping of geomechanical parameters in the northern part of Krishna-Godavari (K-G) offshore. Well logs such as: gamma ray (GR), resistivity (Rt), density (ρ), compressional to shear wave velocity (Vp/Vs) are considered for estimation of E, ν, pore pressure, in-situ stress and brittleness coefficient in the Raghavapuram Shale reservoir in this basin. Cretaceous containing mainly the Raghavapuram Shale forms the unconventional hydrocarbon reservoir in this basin. The total organic content (TOC) of this shale ranges from 0.8% to 6.4% (Tewari and Singh, 2009).

Results and Discussion

The geomechanical properties or elastic constants such as: E and ν will vary within the Raghavapuram Shale reservoir. The dynamic elastic constants of E and ν have been estimated for the depth interval of 410 to 1479 m and 1200 to 1650 m from density and Vp/Vs for the well W-1 and W-2 respectively. The dynamic Poisson's ratio (υ_{dyn}) ranges from 0.25 to 0.35 and 0.28 to 0.32 for the Raghavapuram Shale for well W-1 and W-2 respectively. The value of dynamic E (E_{dyn}) ranges from 12.5 to 23.0 GPa and 12.0 to 27.0 GPa for the Raghavapuram Shale for W-1 and W-2 respectively (Figures 2 and 3). Figures 4, 5 and 6 are showing the estimated E, ν and brittleness coefficient mapped in the post-stack seismic section-X. The cross-correlation, training error and validation error for MLFN models of predicting vertical stress, PP and minimum horizontal stress are shown in Table 1.

Table 1: cross-correlation, training error and validation error for MLFN models of predicting vertical stress, PP and minimum horizontal stress.

Stress	Cross-correlation	Training Error (MPa)	Validation Error (MPa)
Vertical Stress (σ_V)	0.98	1.18	1.86
Pore Pressure (PP)	0.81	0.79	1.40
Minimum Horizontal Stress (σ_h)	0.95	1.07	0.50

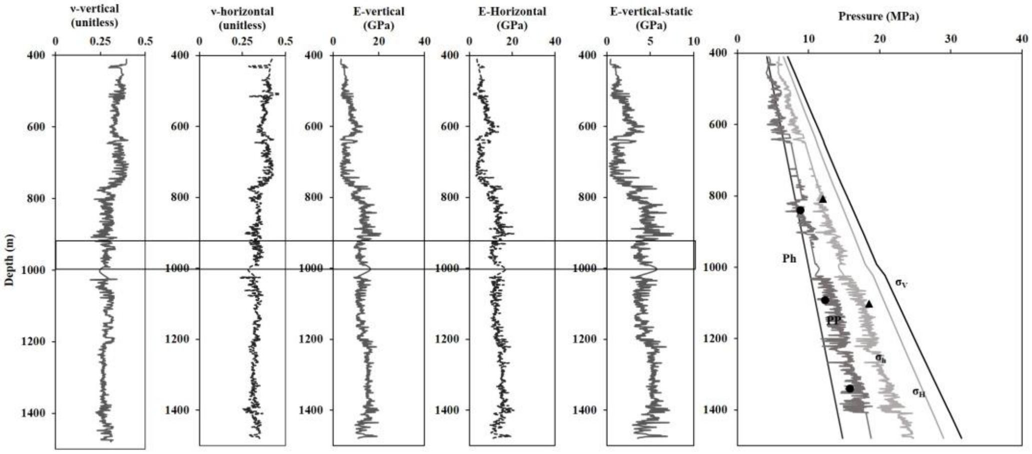

Figure 2: **:** Dynamic vertical and horizontal Poisson's ratio (ν), dynamic vertical and horizontal Young's Modulus (E) and stress profile (hydrostatic pressure (P_h), pore pressure (PP), minimum horizontal stress (σ_h), maximum horizontal (σ_H) and vertical stress (σ_V)) for well W-1 for the selected depth interval 400-1479m. Repeat formation tester (RFT) data (●), leak-off-test (LOT) data (▲) have been shown to validate pore pressure and minimum horizontal stress.

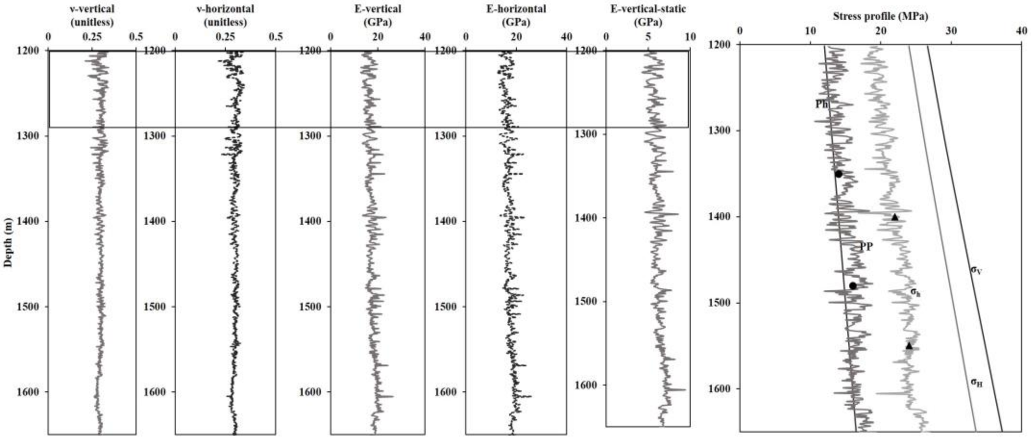

Figure:3 Dynamic vertical and horizontal Poisson's ratio (ν), dynamic vertical and horizontal Young's Modulus (E) and stress profile (hydrostatic pressure (P_h), pore pressure (PP), minimum horizontal stress (σ_h), maximum horizontal (σ_H) and vertical stress (σ_V)) for well W-2 for the selected depth interval 1200-1650m. Repeat formation tester (RFT) data (●), leak-off-test (LOT) data (▲) have been shown to validate PP and σ_h.

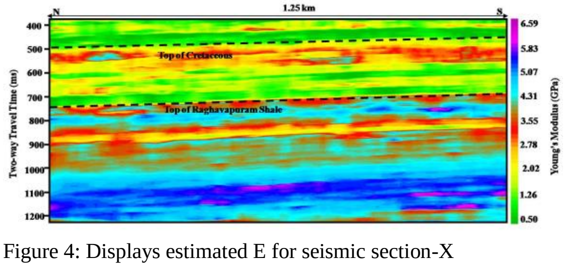

Figure 4: Displays estimated E for seismic section-X

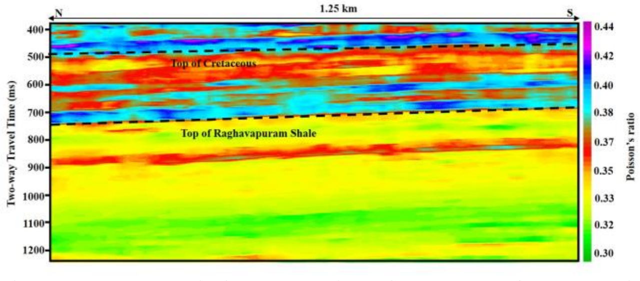

Figure 5: Displays estimated ν for section-X.

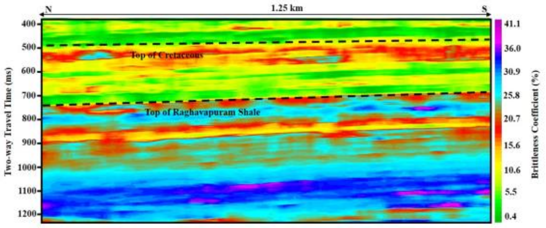

Figure 6: Illustrates brittleness coefficient for section-X.

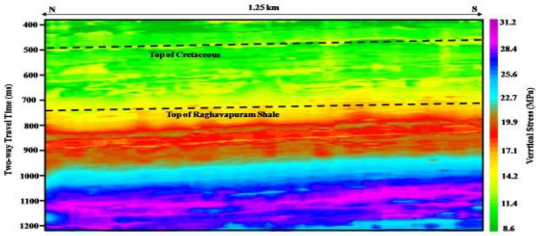

Figure 7: MLFN predicted vertical stress within time window 400-1200ms.

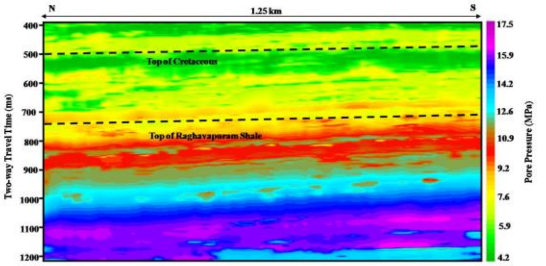

Figure 8: MLFN predicted pore pressure within time window 400-1200ms.

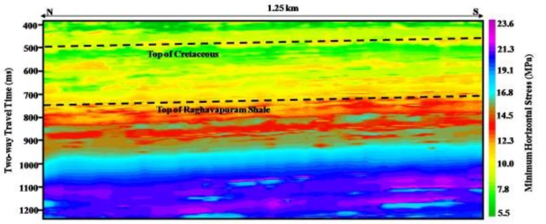

Figure 9: MLFN predicted minimum horizontal stress within time window 400-1200ms.

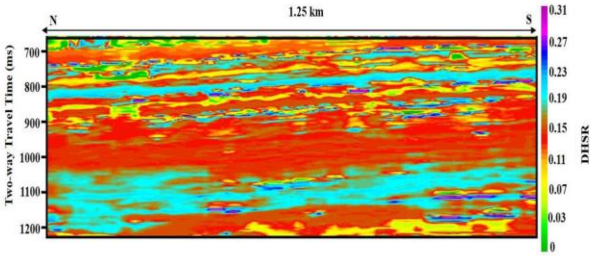

Figure 10: Mapping of DHSR in the Raghvapuram Shale.

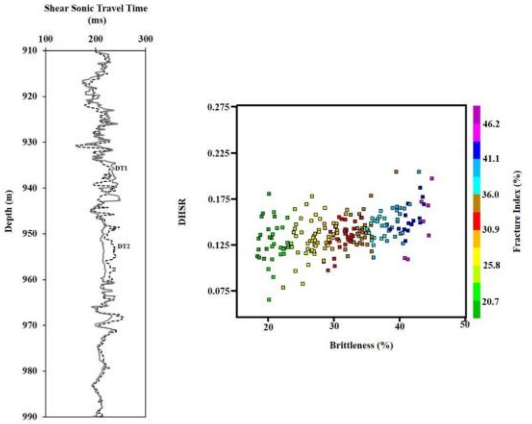

Figure 11: Displaying the fast and slow shear wave travel times through the Raghavapuram Shale and crossplot between brittleness and DHSR color coded with fracture index computed from dipole shear sonic log.

Top of Raghavapuram Shale is observed at 750ms in the seismic section X. Vertical stress is increasing ranging from 8.6 to 31.2 MPa in the time interval 400-1200ms (Figure 7). Pore pressure is mostly hydrostatic ranging from 4.2 to 17.5 MPa within time window 400-1200ms (Figure 8). Minimum horizontal stress is increasing with depth ranging from 5.5 to 23.6 MPa for line X within time window 400-1200ms (Figure 9). DHSR is ranging from 0.07 at 750ms to maximum 0.20 at 1200ms for seismic section X (Figure 10). Higher values of brittleness coefficient indicate rocks that are more likely to fracture and lower values of the DHSR have an intersecting fractures tendency. This DHSR and brittleness coefficient maps are correlated with fracture index obtained from dipole shear sonic log to have an idea of fracture type in this reservoir. The brittleness of 20 to 45% and DHSR of 7-16% with 20-46% fracture index are noticed in the Raghavapuram Shale (Figure 11).

Conclusions

This work demonstrates an approach of estimating pore pressure, in-situ stress, DSHR and brittleness from post-stack seismic data in the Raghavapuram Shale. Pore pressure and vertical stress mapping in the Raghvapuram Shale is implemented for DHSR mapping. Average brittleness coefficient is computed from static E and ν sections. Fractures are aligned in high DHSR zones and oriented to the direction of maximum horizontal stress. Output of this work may help in completion and fracture stimulation design for exploitation of resources from unconventional shale reservoir.

References

Altamar, R. P., and K. Marfurt (2015),Identification of Brittle/Ductile Areas in Unconventional Reservoirs Using Seismic and Microseismic Data: Application to the Barnett Shale, Interpretation, 3 (4), T233-T243.

Aminian, K., S. Ameri **(**2005), Application of artificial neural networks for reservoir characterization with limited data, Journal of Petroleum Science and Engineering, 49, 212–222.

Chatterjee, R., and M. Mukhopadhyay (2002), In Situ Stress Determination using Well Log Data for the Oil Fields of the Krishna-Godavari Basin, India, Petrophysics, 43(1), 26-37.

Chatterjee, R. (2008), Effect of normal faulting on in-situ stress: A case study from Mandapeta Field, Krishna-Godavari basin, India, Earth and Planetary Science Letters, 269 (3), 458-467.

Chatterjee, R., M. Mukhopadhyay, and S. Paul (2011), Overpressure zone under the Krishna–Godavari offshore basin: geophysical implications for natural hazard in deeper-water drilling, Natural Hazards, 57(1), 121-132.

Das, B., R, Chatterjee (2017), Wellbore stability analysis and prediction of minimum mud weight for fewwells in Krishna-Godavari Basin, India, International Journal of Rock Mechanics and Mining Sciences, 93, 30-37.

Eaton, B. A. (1972), Graphical method predicts geopressures worldwide, World Oil, 182, 100-104.

Fjaer, E., Holt, R. M., Horsrud, P., Raaen, A. M. and Risnes, R. (2008), Petroleum related rock mechanics, Development in Petroleum Science, Elsevier.

Gholami, R., Rasouli, V., Aadnoy, B. and Mohammadi, R. (2015), Application of in situ stress estimation methods in wellbore stability analysis under isotropic and anisotropic conditions, Journal of Geophysics and Engineering, 12, 657-673.

Gray, D., P. Anderson, J. Logel, F. Delbecq, D. Schmidt, and R. Schmid (2012), Estimation of stress and geomechanical properties using 3D seismic data, First Break, 30, March.

Kaydani, H., A. Mohebbi, A. Baghaie (2012), Neural fuzzy system development for the prediction of permeability from wireline log data based on fuzzy clustering, Petroleum Science and Technology ,30, 2036–2045.

Liu, Z., and J. Liu (1998), Seismic-controlled nonlinear extrapolation of well parameters using neural networks, Geophysics, 63, 2035–2041.

Mc Cormack, M. D. **(**1991), Neural computing in geophysics: The Leading Edge, 10, 11–15.

Rickman, R., M. Mullen, E. Petre, B. Grieser, and D. Kundert (2008), A practical use of shale petrophysics for stimulation design optimization: all shale plays are not clones of the Barnett Shale, SPE, Annual Technical Conference and Exhibition, Denver, Colorado, USA, 21-24 September, SPE 115258, DOI: 10.2118/115258-MS.

Russell, B., and D. Hampson (1991),Comparison of poststack inversion methods, 61st Annual International Meeting, SEG, Houston, Texas, Expanded Abstracts, 10, 876-878.

Singha, D. K., and R. Chatterjee (2015),Geomechanical Modeling using Finite Element Method for Prediction of In-situ Stress in Krishna-Godavari basin, India. International Journal of Rock Mechanics and Mining Sciences, 73, 15-27.

Tewari, M. K., and B. Singh (2009),Strategy for identifying the Hydrocarbon prospects in tight /Shaly Silty reservoirs-An integrated approach a case study, 2nd SPWLA-India Symposium, November 19-20, 2009, SPWLA, India.

Zehnder, A. T. (2012), Fracture Mechanics, Springer, DOI: 10.1007/978-94-007-2595-9.

Zhang L. (2011), Three-dimensional numerical models of drilling induced core fractures. MSc thesis. University of Alberta.

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