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Analysis of Elastic Geomechanical Properties Derived From Well Log and Seismic Data, Using Artificial Intelligence (ANN): A Case Study of "AJAH" Field Offshore Niger Delta

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Abstract:
Elastic Geomechanical properties are key elemental properties that must be adequately predicted for wellbore stability and effective hydraulic fracturing to be assured. Understanding these properties is key for planning drilling, production and reservoir management. This research analyses elastic Geomechanical properties predicted by seismic and well log data in "AJAH" field offshore Niger Delta using Artificial Neural Network. Analysis of well logs (5 wells) shows that the Poisson's ratio (V), Shear modulus (G), Young's modulus (E), Bulk modulus (K), Compressibility (β) and Unconfined compressional strength (UCS) range from 0.11- 0.47, 0.15 – 8.5$\times 10^{10}$pa, 0.15 –14.3 $\times 10^{10}$pa, 0.49 – 3.1 $\times 10^{10}$pa, 0.32 – 2.0 $\times 10^{-8}$pa^{-1} and 0.08 – 5.77 $\times 10^{7}$pa respectively. A plot of Poisson's ratio Vs Young's modulus shows brittleness, indicating that hydraulic fracturing within this field would be very challenging. A well trained Artificial Neural Network (ANN) was used to predict elastic geomechanical properties in the vicinity of the wells and later was used to populate the estimated properties across the field. The ANN showed a correlation of 0.80205, 0.69493, 0.70674 and 0.67354 for Poisson's ratio, Shear modulus, Young's modulus and Bulk modulus respectively, indicating a good match. ***.*** *The ANN revealed that Shear modulus, Young's modulus and Bulk modulus generated by seismic is relatively greater than the one generated by well logs with a factor of $\times 10^{4}$ while Poisson's ratio is approximately the same. This research shows that in a data handicapped area (especially during exploration) a 3D seismic when constrain with well logs is very useful in predicting elastic geomechanical properties for planning/guiding new drills and for making inform reservoir management decisions.*
Key words*: Elastic geomechanical properties, ANN, Well logs, Seismic data, Wellbore stability*

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I. Introduction

Geomechanical (elastic and inelastic) properties are key elemental parameters that must be precisely predicted for wellbore stability to be assured. According to [1], the oil industry spends about 10billion dollars yearly on borehole instability issues. Elastic geomechanical property is the property of a rock that allows it to produce some form of resistance to deformation (shape or volume). When this elastic limit is exceeded, the material tends to break (deformation) and this deformation could lead to a lot of well instability issues. Significant amount drilling and completion budget is spent addressing wellbore issues/instability [2].

Geomechanical parameters includes: Pore pressure, Poisson's ratio (V), Shear modulus (G), Young's modulus (E), Bulk modulus (K), Compressibility (β) and Unconfined compressional strength (UCS), fracture gradient etc. and they are best estimated in the laboratory using static method (core information) but because cores are expensive, these parameters are now routinely estimated by the extraction of density (ρ), compressive (V_p) and shear (V_s) wave velocities from Well information, or by the extraction of interval velocity from seismic or from drilling data (dynamic). There are several available empirical correlations that allows the estimation of desired geomechanical properties from the extracted primary properties. The elastic values obtained from both static and dynamic are seen to vary significantly owing to the effect of wave propagation (variation in time due to differences in frequency), scale effect or the effect of seismic data processing (as stacking results to reduction of velocity).

Different geological materials have different mechanical strength and this mechanical strength varies from locality to locality even for similar lithologic unit. Reference [3] stated clearly that this variation could be due to variation of over burden weight, grain cementation strength, fluid pressure, rate of flow, fluid type, pressure gradient or even stress caused by geological conditions (processes of sedimentation/deposition and environment of deposition). Changes in elastic rock properties lead to resultant changes in horizontal in-situ stresses [4]. In-situ stress and elastic geomechanical properties are therefore one of the major controls of fracture simulation behavior/production efficiency. Understanding of these geomechanical properties will aid in reducing uncertainties that relates to predicting wellbore fracture gradient, Formation in-situ pressure and general reservoir rock property (ductileness or brittleness). Furthermore, understanding these information from offset location will go a long way in ensuring optimum well placement, efficient hydraulic fracturing and effective completion design [5].

Seismic data contains important information about structure, stratigraphy, Petrophysical and geotechnical features of the subsurface and this information can be analyzed to yield important elastic mechanical properties of the subsurface (reservoir) rock. But first the seismic data must be calibrated with well logs and if possible, with core data to improve it prediction efficiency. Then the seismic will be inverted using appropriate inversion software. Well logs have proved very useful in estimating elastic geomechanical properties especially with the availability of different important empirical equation linking different elastic rock modulus with the lame's parameter. Logs like Sonic, density, resistivity and gamma have found themselves useful in estimating elastic properties of rock.

Artificial neural network is a set of high definition machine algorithms designed just like the human brain, to be able to understand pattern and perfectly mimic them [6]. Its main objective is to pick patterns and understand its relationship in other to cluster and classify properties based on the similarities picked. In the past, two major approaches have been used for this goal: classical statistics and knowledge from experts. However, the number of human experts is limited, and they may overlook important details, while classical statistical analysis does not give adequate answer when large amounts of complex data are available. The alternative is to use high definition machine language and artificial intelligence to analyze patterns, extract useful information in other to distribute properties [7]. Planning of drilling activities (mud weight design, in-situ stress state knowledge) is becoming very challenging especially in data handicapped areas (during exploration) due to the difficulty in accurate prediction of geomechanical properties. This research is therefore aimed at analyzing elastic geomechanical properties predicted by well logs and seismic using Artificial Neural Network and proceeds in distributing the predicted properties across the field, centered at trying to reduce uncertainty in predicting elastic geomechanical properties.

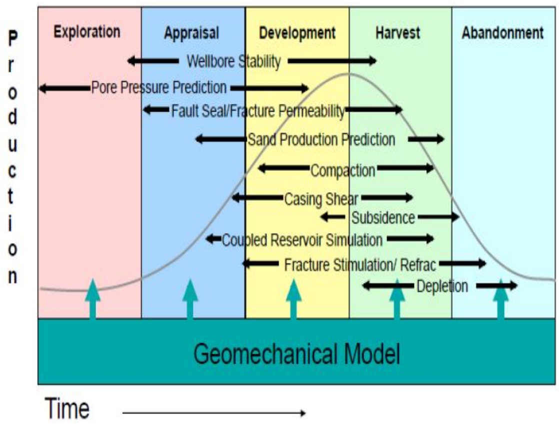

Fig 1: Geomechanics throughout the life of a Field [8]

II. Geology

The word "Delta" represent a piece of environment close to the ocean, Niger delta is therefore a piece of environment situated at the Peak of the Guinea in the West Coast of Africa. This Basin was formed in the late Jurassic as a result of the rifting of the South America and Africa plate [9]. Originally, the Cenozoic delta was formed at the intersection between the Benue trough and the South Atlantic Ocean and it represent the youngest sediment in the failed arm of the triple junction. The early created Delta was short of sediment as major sediment emplacement only started in the tertiary time, with sediment coming from weathered upland (continental sediment) through the Niger-Benue drainage basin [11]. Subsequently the Delta back stepped basinward toward the coast of Gulf of Guinea as presently seen today [11], [12]. The present-day Delta is said to be wave dominated with tidal influence implying that major sediment supply was as a result of wave action. Reference [10], explained that outbuilding of the Delta results to different successive growth called the depobelt and that this depobelt is younging basinward. Irrespective of the depobelts the tertiary Niger Delta is composed of three Formations; the under compacted, un-dewatered, over pressured Akata Formation, the paralic Agbada and the Continental sand (Benin Formation). Extending to an area span of approximately seventy-five thousand square kilometers with average thickness pile of 11,000m [13], [14], [15].

The Akata Formation represent the oldest of the three Formations and it is located at the bottom of the delta, made up of marine shale with little sand and silt. The unit is of Paleocene to recent in age and it represent a thick body of under compacted and over pressured shale formed during the low stand system tract when terrigenous material was transported deep offshore [16], with thickness of about 7km [10]. The Agbada Formation consist of sand with some intercalation of shale bodies, this unit is of Eocene-recent in age and rests directly on the Akata shale. The sediments here show a transitional regime consisting of the lower deltaic plain and the coastal barrier with an average of about 50% sand units. This Formation is believed to be the reservoir hosting the rich hydrocarbon resources of the Niger Delta. Unit of this sand are interrupted by shale of varying thickness, researchers believe this shale to be the seal or cap rock helping in the entrapment of hydrocarbon [15], [17]. The structures found in the Agbada include the roll over anticline, collapse crest and growth fault which flattens with deeper burial [18]. The Benin Formation consists of massive continental sand deposit with little slit, lignite streams, shale and pockets of clay deposit. This unit is the believed to be of Eocene to recent in age and the sand body compose of large grain size that is moderately sorted. The sediment pile of this Formation is roughly 2000m thick and varies from locality to locality within the delta [13].

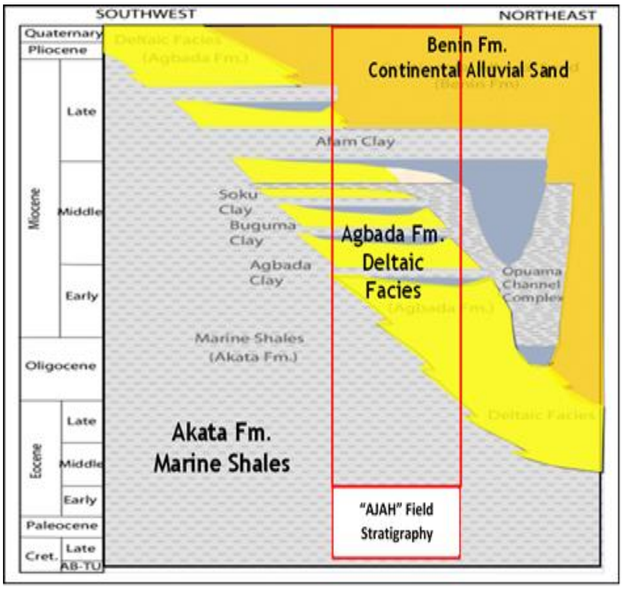

Fig 2: Stratigraphic succession of the study area [10]

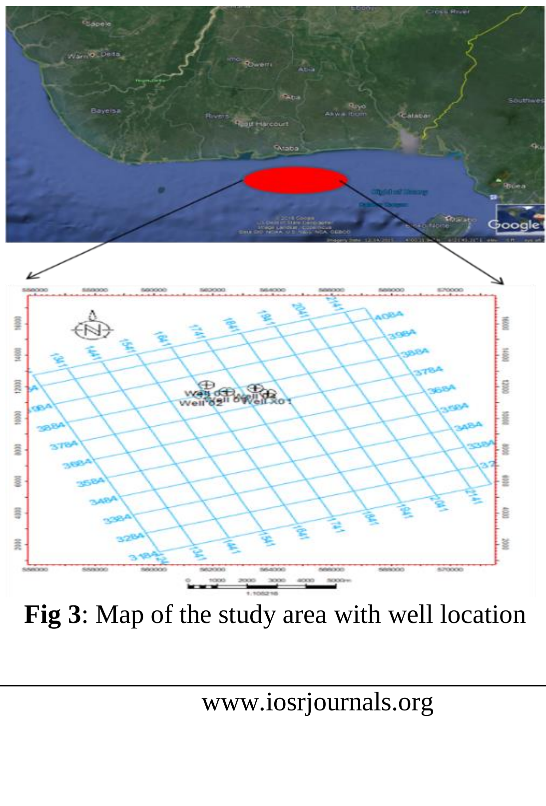

Fig 3: Map of the study area with well location

III. Methodology

This research involves the integrating well logs with seismic data, for prediction of elastic geomechanical properties. For the logs empirical correlations were available for estimating elastic properties, whereas check shots were used to calibrate the sonic log. Sonic and density were then used for well-seismic tie in other to extract the wavelet which was in turn used for seismic inversion. The inverted acoustic impedance was use as base information for the generation of other rock properties. A well trained Artificial Neural Network was used for the prediction of elastic geomechanical properties taking information from seismic and well logs. The estimated rock properties include: Shear modulus, Bulk modulus, Poisson's ratio, UCS, Young's modulus and Compressibility modulus.

Assumptions

In the course of this research some assumption was made, and they include:

1. Anisotropic effect is ignored
2. Rock properties are assumed to be homogenous
3. The five wells are enough for distributing elastic properties across the Field

Estimating geomechanical elastic properties from well logs

Estimation of geomechanical elastic properties of rock from well logs is the most direct, most convenient and most common dynamic method. Compressional wave velocity was extracted from the sonic log and localized V_p –V_s correlation used to compute the shear wave velocity [19]. Other empirical correlation was used for obtaining the different elastic properties [20], [21], [22], [23].

$$V_p = \frac{1000000*0.305}{\Delta_{tc}} \quad (1)$$

$$V_p = \frac{1000000*0.305}{\Delta_{ts}} \quad (2)$$

$$V_p = 1.11702V_s + 1279.08 \quad (3)$$

$$V = \frac{0.5(\frac{\Delta t_s}{\Delta t_c})^2 - 1}{(\frac{\Delta t_s}{\Delta t_c})^2 - 1} \quad (4)$$

$$G = \frac{E}{2} + 2V \quad (5)$$

$$E = \rho V_s^2 \left(\frac{3Vp2 - 4Vs2}{Vp2 - Vs2}\right) \quad (6)$$

$$K = \frac{E}{3} + (1 - 2V) \quad (7)$$

$$UCS_{Sh} = 1.35 * (304.8/\Delta t)^{2.6} \quad (8)$$

$$UCS_{Sst} = 1200exp(-0.036\Delta t) \quad (9)$$

G=Shear modulus, K= bulk modulus, V=Poisson's ratio, E= Young's modulus, V_s= secondary velocity, V_p= primary velocity, Δt_c= primary wave transit time Δt_s = secondary wave transist time

Estimating rock elastic properties from seismic

Estimation of elastic properties from seismic is done be inverting the seismic (seismic inversion) to produce and Acoustic impedance log which was used for the inversion of elastic rock properties. The post stacked seismic processed data was used. The elastic rock properties logs were generated using the relationship below:

$$AI = \rho V_p \quad (10)$$

$$SI = \rho V_s \quad (11)$$

Creating and Training Artificial Neural Network

Artificial neural network is a set of high definition machine algorithms designed just like the human brain, to be able to understand pattern and perfectly mimic them [24]. Its main objective is to pick patterns and understand its relationship in other to cluster and classify properties based on the similarities picked. For the purpose of this research well 01 -04 was used to train the Network, reason for choosing these wells was because they all fall on the same inline/cross line and could possibly share similar properties. The Artificial neural network training involves exposing the network to series of elastic properties around the wells using different attributes and different operator lengths. There about several attribute, so training involves selecting these attributes that has a relationship with the elastic properties of interest. What the network does is to put all the attributes together and find a way to mimic the property already estimated by the well logs. After a network for an elastic property was created, a level of mimic known as match correlation was then observed. Several networks were trained for each elastic property. After creation of several networks, the network that gave the best fit was then adopted.

Validation of trained Artificial Neural Network

The adopted trained network was then validated using well X01, reason for this is because the well was not used for training and because it lies on a different inline and cross line. ANN validation is just a way of confirming the authentication of the trained network. This involves using the network to predict elastic properties at well X01 and then comparing the predicted property with the original properties of well X01.
The validated network was then used to populate the generated elastic properties across the seismic volume. After which across plots of the seismic Vs well logs elastic properties were also done.

IV. Results and Discussion

Elastic Geomechanical properties from logs and Seismic

The investigated interval from the well log ranges from 1000ft – 9400ft in the subsurface and it is made of alternation of sand shale sequence typical of Agbada Formation. The elastic rock properties were estimated using empirical correlations (equation 1-11). Table 1 shows the summary of the generated properties. As earlier stated, the ANN was constrained with the well logs and used to generate elastic geomechanical properties within the seismic volume. This was done by first inverting the seismic to produce an inverted acoustic/elastic impedance log using density and velocity information. The impedance logs were then used to generate elastic properties logs. The ANN then used several seismic attributes to predict the elastic rock properties in the vicinity of the wells (Cropped seismic volume) and was finally applied on the entire seismic volume. Figure 4. shows the generated elastic geomechanical properties within the seismic volume.

Young's Modulus and Poisson's ratio

Young modulus which indicates the ability of a material to withstand deformation ranges from 5758Mpa – 48222mpa and 1487Mpa – 84557Mpa for shale and sand respectively. The smaller lower limit values of the sand suggest that the sand is loose, soft and unconsolidated, since the sand displaying this reading are shallow seated (less than 2000ft) they are suggestive of Benin sand. Generally, sands are more elastic than shales (due to mineralogy and composition) this explains why sand values for Young's modulus are higher than shale. Young's Modulus for seismic ranges from $4.85*10^7$ $-1.43*10^8$ Mpa as against well derived Young's Modulus ($5.758*10^3 – 4.822*10^4$ Mpa) with an average factor of $*10^4$. This implies that in this field it is possible to convert Young's modulus derived from seismic to well log by dividing with a factor of $*10^4$, this would be very handy especially in guiding new drills away from the vicinity of the previous wells.

Table 1: Summary of rock elastic properties estimated from well logs

WELLS	PARAMETER	SHALE	SAND
WELL 01	V	0.11 – 0.31	0.12 - 0.45
	G (Mpa)	3856 - 20782	834 – 18319
	E (Mpa)	10146 - 48222	2341 -41060
	K (Mpa)	3381 - 14506	809 – 13685
	USC (Mpa)	11.8 – 28.3	1.2 – 44.7
WELL 02	V	0.21 – 0.36	0.23 – 0.38
	E (Mpa)	6240 - 18215	4825 – 31351
	G(Mpa)	2646 - 8145	1745 – 13549
	K (Mpa)	2400 - 18884	1607 – 31351
	UCS (Mpa)	8.2 – 19.1	5.4 – 44.3
WELL 03	V (Mpa)	0.21 – 0.29	0.23 – 0.38
	E (Mpa)	11787 -20978	6212 – 13823
	G (Mpa)	4550 - 8929	2228 – 5491
	K (Mpa)	3928 - 6991	2039 – 5667
	UCS(Mpa)	13.1 - 19	5.8 – 24
WELL 04	V	0.2 – 0.39	0.25 – 0.39
	E (Mpa)	5758 - 26866	1774 – 29629
	G (Mpa)	2068 – 11379	1774 – 12790
	K (Mpa)	1918 - 8954	1654 – 9875
	UCS (Mpa)	7.4 – 2.2	4.19 – 37
WELL XO1	V	0.12 – 0.35	0.14 – 0.47
	E (Mpa)	7498 - 43199	1487 – 84557
	G (Mpa)	2780 – 19262	506 – 39646
	K (Mpa)	2499 – 143 98	494 – 28184
	UCS (Mpa)	9.8 – 27.4	0.8 – 56.7

Figure 5 shows a cross plot of Young's Modulus of well 01 versus seismic and well X01 versus seismic at in-line 3138. It is worthy to note that cross plots were done for the five wells (Well 01-X01) but only two wells were displayed here (one well used for training of the network and another used for validating the network). The average correlation for the five wells versus seismic is 0.73509 indicating a good match (see table 3).

Poisson's ratio is the ratio of transverse strain to axial strain. Poisson's ratio is an important mechanical property that is used to predict the geomechanical behavior during drilling or enhancement activities. Well bore stability, sand production and hydraulic fracturing are strongly affected by strength of the rock which can be determined by the Poisson's ratio [25]. Reservoir volume changes due to production, injection or subsequent uplift or subsidence can be very substantial hence a good understanding of the Poisson's ratio will help in handling this effect [26]. The estimated Poisson's ratio from well logs ranges from 0.11 – 0.39 for shale and 0.12 – 0.47 for sand. It can be observed that the Poisson's ratio generally decreases with depth within similar lithology, since compaction generally increases with depth (for an undisturbed Formations).

The estimated Poisson's ratio from seismic, ranges from 0.33 – 0.456 with the lower boundary significantly different from that of the well logs. Explanation for this is that the seismic carries out averaging of attribute to arrive at the estimated Poisson's. Only few well intervals showed Poisson's ratio that are within 0.11- 0.3 as majority of the estimated Poisson's ratio lies between 0.3- 0.45. Therefore, an average value, let say for every 200m square volume is likely to be above 0.3.

Table 2: Summary of the correlation of elastic properties of Seismic Vs Well log

properties	**Well 01**	**Well 02**	**Well 03**	**Well 04**	**Well X01**	**Ave correlation**
Poisson's ratio	0.89689	0.81923	0.79831	0.64080	0.85504	**0.80205**
Shear modulus	0.65581	0.82665	0.62456	0.55421	0.81342	**0.69493**
Bulk modulus	0.72563	0.78682	0.64352	0.58125	0.79652	**0.70674**
Young's modulus	0.93131	0.81775	0.34630	0.64080	0.93930	**0.73509**

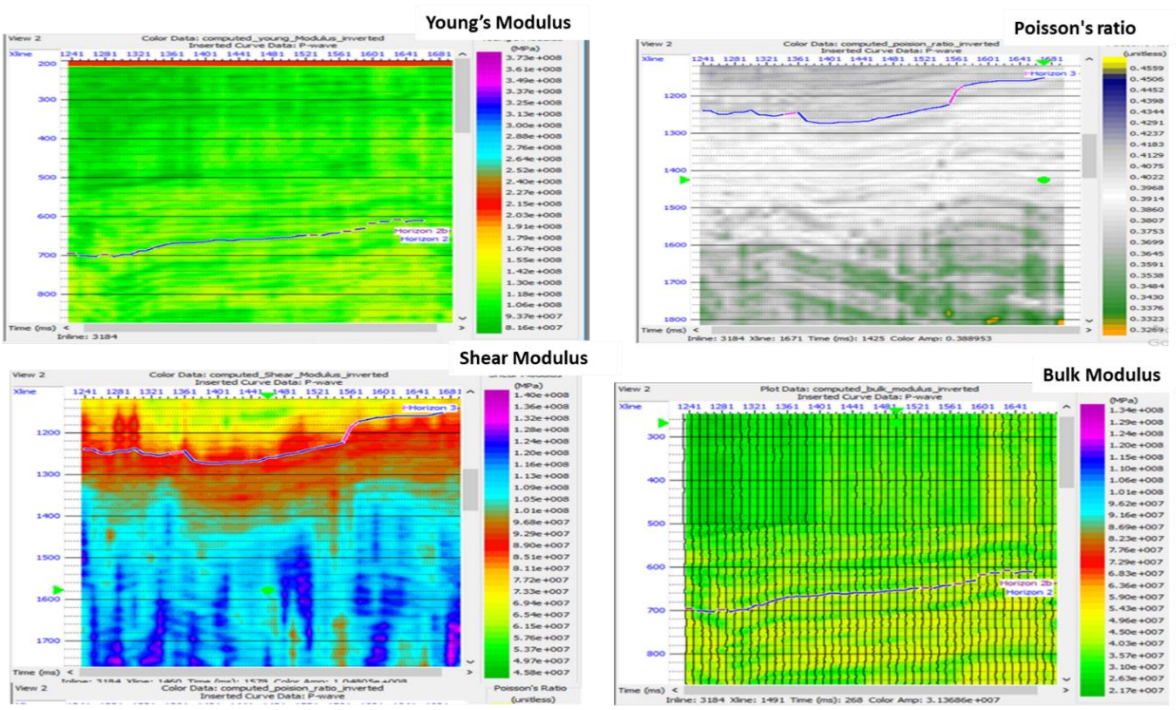

Fig 4: Seismic generated elastic properties on in-line 3138

Shear and Bulk Modulus

The shear modulus (G) is the ratio of the shear stress to the shear strain. It explains the stiffness of a rock. The well logs estimated shear modulus ranges from $2.07*10^4$ – $8.15*10^4$Mpa and $0.51*10^4$Mpa – $39.65*10^4$Mpa for sand and shale respectively, indicating that the sands are stiffer than the shales. The bulk modulus defines how a material will undergo a volume strain when subjected to pressure and varies from $5.1*10^3$Mpa – $2.818*10^4$Mpa and is relatively higher in sands. The seismic predicted property varies from

$8.65*10^7$–$1.93*10^8$ Mpa for shear modulus and $2.17*10^7$ - $6.83*10^7$Mpa for bulk modulus. Reason for the variation of estimated elastic modulus (shear and bulk modulus) could be due to variation in frequency as well logs allows much higher frequencies which means much lower velocity, acoustic impedance and lower elastic modulus.

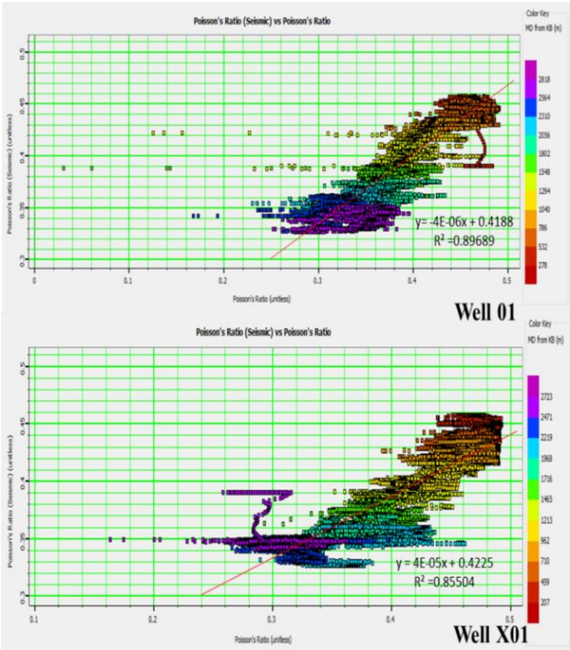

Fig 5: Young's Modulus of log Vs Seismic

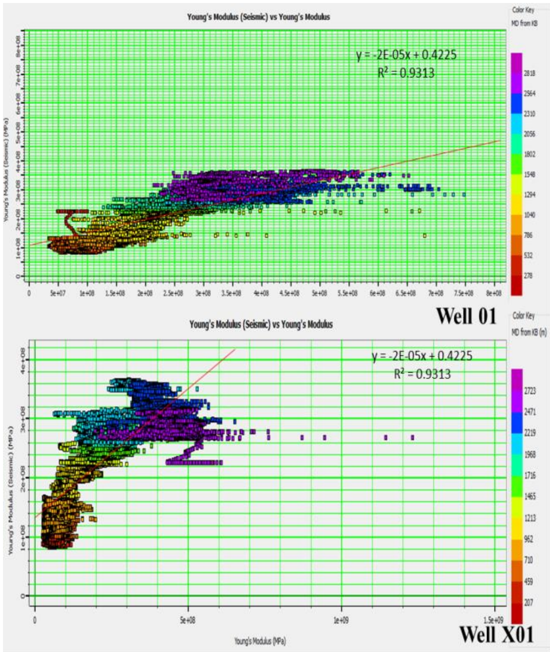

Fig 6: Possion's ratio of Log Vs Seismic

Compressibility and Unconfined compressibility strength

The compressibility (β) ranges from 0.4 – 2.0 $*10^{-8}$ Mpa^{-1} and UCS ranges from 0.8 – 57Mpa. Low compressibility, shear modulus and UCS indicates that deeper seated shales are more stiff, rigid, ductile and are susceptible to compressive failure, but this also means that they would serve as a good barrier to hydraulic stimulator. They, therefore, can easily from a barrier to fracture growth under hydraulic fracturing unlike the brittle sand that will fracture easily.

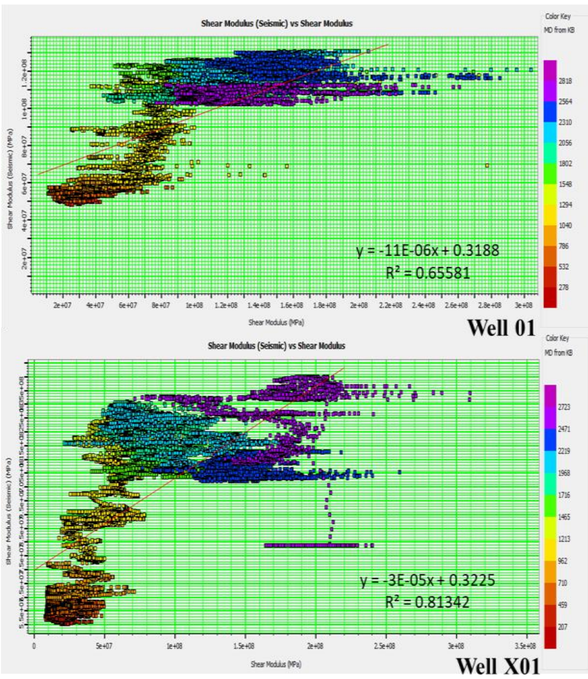

Fig 7: Shear Modulus for Log vs Seismic

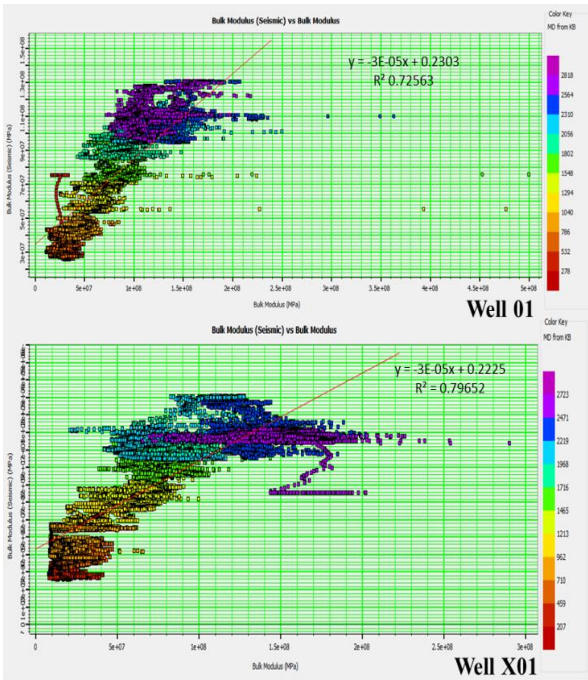

Fig 8: Bulk Modulus for Log vs Seismic

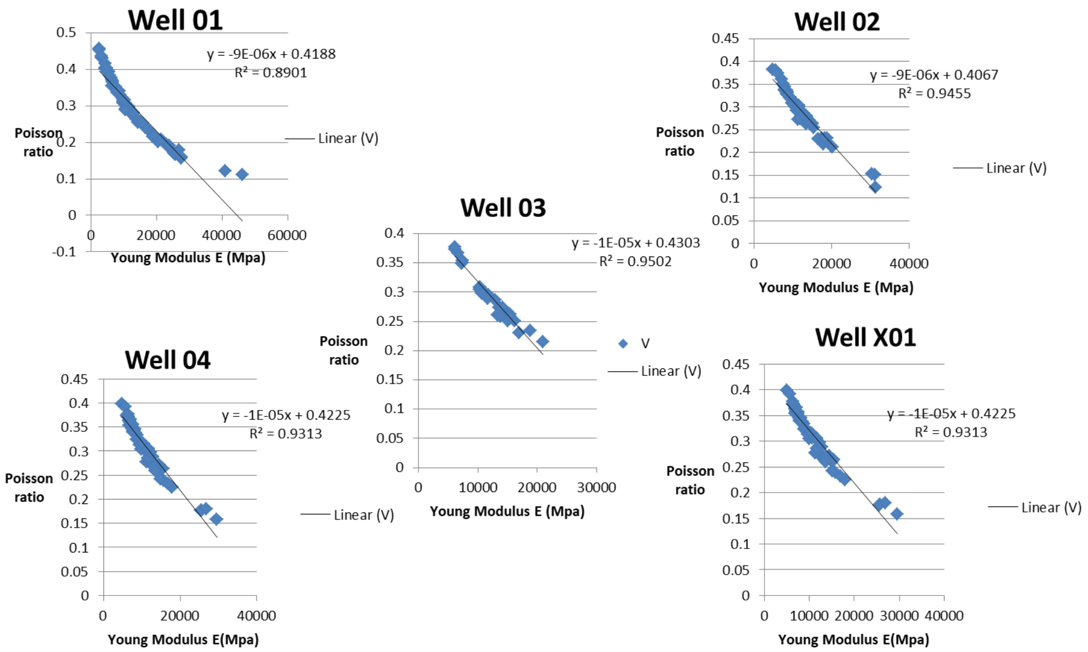

Fig 9: Poisson ratio Vs Young Modulus for well 01-X01

Brittleness and Ductility (Poisson's Vs Young's modulus)

The plot of Poisson's ratio Vs Young's Modulus is an indicator of the brittleness or ductility of any earth material. High Poisson's ratio with low Young's modulus is an indication of brittleness while High Poisson's ratio with high Young's modulus is an indication of ductility. In the study area both the seismic and well log analysis showed a trend of increasing Poisson's ratio with decreasing Young's Modulus indicative of brittleness. The implication of this is that the encountered Formation will easily fracture when subjected to pressure (hydraulic fracturing). In other words, hydraulic fracturing will be very challenging in this area, as reservoir unit can extend the frack instead of acting as a simulator barrier.

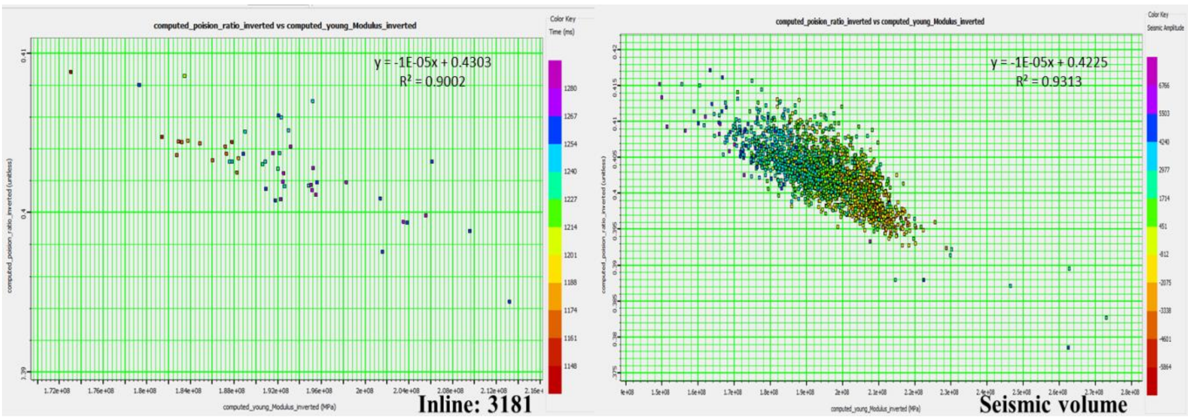

Fig10: Cross plot of Poisson's Vs Young's Modulus for Inline 3181 and in Cropped Seismic Volume

V. Conclusion

The investigated interval from the well log ranges from 1000ft – 9400ft in the subsurface and it is made of alternation of sand-shale sequence typical of Agbada Formation. The estimated Poisson's ratio ranges from 0.18 – 0.47 which it typical of the Niger Delta. The Field is believed to be brittle especially at sand interval and reservoir hydraulic fracturing would prove very challenging but deep-seated shales could act as a simulation barrier since they show evidence of ductility. The Formation is generally loose, soft and unconsolidated. The ANN proved to be very useful in predicting elastic geomechanical properties with an average correlation of 0.734703 for predicted and actual (from wells). Estimated Poisson's ratio is seen to be the most accurately predicted property with a correlation of 0.80205. Within the studied field a conversion factor of $*10^4$ can be used to convert well logs elastic properties to seismic properties and this would be very useful in planning new drills especially in the vicinity away from the previous wells. This research therefore, demonstrates that ANN can be used for accurate prediction of elastic Geomechanical properties where drilling or core information is unavailable.

References

[1]. Erling F, Rune MH, Per H, and Arne MR. Petroleum related rock mechanics, Elsevier Science B.V 1996.
[2]. Abijah FA and Tse AC. Geomechanical Evaluation of an onshore oil field in the Niger Delta, Nigeria IOSR Journal of Applied Geology and Geophysics 2016, 4 (1):99-111.
[3]. Okotie S. and Ichenwo J. Comparative Study of Rock Strength and Petrophysical Properties Derived from Core and Log Data. International Journal of Current Engineering and Technology 2015, 2347 – 5161.
[4]. Gray FD. Elastic Inversion for Lame Parameters. CSEG 2002 National Convention Expanded Abstracts 2002.
[5]. Payne SS, and Meyer J. Using Seismic Inversion to Predict Geomechanical Well Behavior: A Case Study from the Permian Basin. Proceedings of the 5th Unconventional Resources Technology Conference. 2017
[6]. Alkinani HH, Al-Hameedi AT, Dunn-Norman S, Flori RE, Alsaba MT and Amer AS. Applications of Artificial Neural Networks in the Petroleum Industry: A Review. Paper SPE-195072-MS presented at SPE Middle East Oil & Gas Show and Conference Held in Bahrain 2019.
[7]. Hand D, Mannila H and Smyth P. Principles of Data Mining. MIT Press, Cambridge, MA 2001.
[8]. Dosunmu, A. Geomechanics lecture note. Center for Petroleum Geoscience. University of Port Harcourt. Unpublished 2018.
[9]. Whiteman A. Nigeria: Its Petroleum Geology, Resources and Potential: London, Graham and Trotman 1982, 394 p.
[10]. Doust H, and Omatsola E. Niger Delta, *in*, Edwards, J. D., and Santogrossi, P.A., eds., Divergent/passive Margin Basins, AAPG Memoir 48: Tulsa, American Association of Petroleum Geologists 1990, 239-248
[11]. Adesida AA, Reijers TA, Nwajide CS. Sequence stratigraphic framework of the Niger Delta. Paper presented at the AAPG international conference and exhibition, Vienna, Austria 1979.
[12]. Evamy BD, Haremboure J, Kameling P, Knaap WA, Molloy FA, Rowlands P.H. Hydrocarbon habitat of tertiary Niger Delta. AAPG Bull 1978,62:1–39.
[13]. Avbovbo, A. A. Tertiary lithostratigraphy of Niger Delta: American Association of Petroleum Geologists Bulletin 1978, 62:295-300.
[14]. Kulke, H. Regional Petroleum Geology of the World. Part II: Africa, America, Australia and Antarctica: Berlin, Gebrüder Borntraeger 1995, 143-172.
[15]. Short, K. C., and Stauble, A. J. Outline of geology of Niger Delta: American 1965
[16]. Stacher, P. (1995). Present understanding of the Niger Delta hydrocarbon habitat, *in* M. N. Oti and G. Postma, eds., Geology of deltas: Rotterdam, A. A. Balkema 1995, 257–267.
[17]. Ejedawe, J.E. The Eastern Niger Delta: geological evolution and hydrocarbon occurrences. SPDC Internal Report, Exploration Note 1989, 89(02):12-23
[18]. Xiao, H., and Suppe, J. Origin of rollover: American Association of Petroleum Geologists Bulletin1992, 76:509-229.
[19]. Ogagarue, D.O. Localized Vp-Vs relationships for the Niger delta sediments. Pacific Journal of Science and Technology 2008, 9 (2): 558-561.
[20]. Mashinsky E. I. Differences between static and dynamic elastic moduli of rocks: Physical causes. Russian Geology and Geophysics2003, 44(9):953–959
[21]. Fjær E., Holt R. M., Horsrud P., Raaen A. M., Risnes R. Petroleum Related Rock Mechanics. 2nd Ed. Elsevier. Amsterdam2008, 514.
[22]. Herwanger J., Koutsabeloulis, N. Seismic Geomechanics: How to Build and Calibrate Geomechanical Models using 3D and 4D Seismic Data. EAGE Publications2011.
[23]. Jedrzejowska-Tyczkowska, H., Slota-Valim, M. Mechaniczny Model Ziemi – jakonowyikoniecznywaruneksukcesuwposzukiwaniach i eksploatacjizlozniekonwencjonalnych. Nafta-Gaz 2012, 6: 329–340.
[24]. McCulloch, W., Walter, P. Alogical calculus of ideas immanent in nervous activity. Bulletin of mathematical biosphysics1943, 5(4) :115 -133.
[25]. Kumar, J. The Effect of Poisson's Ratio on Rock Properties: The 51st Annual Fall Technical Conference and Exhibition of the Society of Petroleum Engineering of AIME, SPE 1976, 6094.
[26]. Stancliffe, R.P. and Kooij, W.A. The use of Satellite-based Radar Interferometry to Monitor Productivity at the Cold Lake Heavy Oil field, Alberta Canada, AAPG,2001,85:781-793.

Nnamdi J. Ajah, et., al. "Analysis of Elastic Geomechanical Properties Derived from Well Log and Seismic Data, Using Artificial Intelligence (ANN): A Case Study of "AJAH" Field Offshore Niger Delta." *IOSR Journal of Applied Geology and Geophysics (IOSR-JAGG)*, 8(1), (2020): pp. 19-27.