Webinars

Welcome!

The program will begin soon.

You will not hear audio until we begin.

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Prediction of Geomechanical Parameters in Real-Time Using Machine Learning While Drilling

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May 27th 2021

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Ouline

- Introduction to Geomechanics
- Determination of Geomechanical Parameters
- Artificial Intelligence Techniques
- AI Applications
- Case Study
- Summary

4

What Is Geomechanics?

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- Geomechanics (from the Greek prefix geo- meaning "earth") involves the study of the mechanics of soil and rock.
- Rock mechanics is generally theoretical and applied science that describes the mechanical behavior of the rock when different stresses are applied.
- The fundamental rock mechanics parameters include:

Elastic Properties	Failure Parameters
• Young's Modulus • Poisson's Ratio	• Compressive Strength • Tensile Strength • Friction Angle

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Importance of Geomechanical Parameters

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- Rock elastic properties has an essential role in:
  - Hydraulic Fracturing Design,
  - In-situ Stresses Estimation,
  - Drilling Performance,
  - Wellbore Stability,
  - Building the Geomechanical Models.
- Rock failure is a geomechanical feature causes many downhole problems such as solids production and wellbore instability issues.
- The availability of rock strength data of the downhole formations is significant for:
  - Optimizing the Drilling Operation Performance,
  - Bit Hydraulics,
  - Determining the Proper Mud Weight while Drilling, and
  - Avoiding Wellbore Instability Issues.

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6

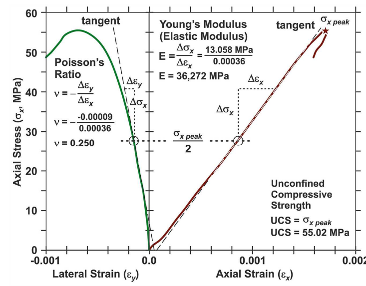
Definitions

- Elastic properties identify the ability of the rock to recover from a deformation caused by external forces and define the relationship between these forces and the resulted deformation.
- Young's modulus (E) is an elastic constant named after British physicist Thomas Young (1773 to 1829) that indicates the rock stiffness and is defined by the ratio between the strain and the stress

$$E = \frac{\sigma}{\varepsilon} = \frac{F/A}{\Delta L/L}$$

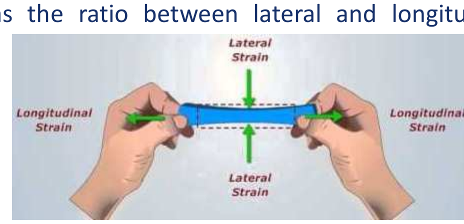
Where

E = Young's modulus
F = longitudinal force
A = area
ΔL = change in length
L = original length
σ = longitudinal stress
ε = longitudinal strain



Definitions

- Poisson's ratio (v) is an elastic feature defined as the ratio between lateral and longitudinal deformation.



- Poisson's ratio (v) can be estimated experimentally (static) or derived (dynamic) from acoustic velocities (V_P and V_S) as follows:

$$\nu_{dyn} = \frac{V_P^2 - 2V_S^2}{2(V_P^2 - V_S^2)}$$

- Poisson's ratio for
  - ✓ Carbonate rocks is ~0.3, for
  - ✓ Sandstones ~0.2, and greater than 0.3 for shale.

Definitions

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- Unconfined compressive strength (UCS) is an essential mechanical rock-parameter for building geomechanical models.
- It defines the maximum compressive stress limit that the rock can endure without failure when uniaxial loading is applied under confinement conditions.

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9

Determination of Geomechanical Parameters

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- Rock mechanical properties can be determined directly using experimental tests conducted on retrieved core samples.
- Rock strength can be estimated in the laboratory using different tests such as
  - Uniaxial Compressive Strength Test,
  - Triaxial Compressive Strength Test,
  - Scratch Test,
  - Schmidt Hammer Test, and
  - Point Load Test.
- Poisson's ratio is ranging from 0.0 to 0.5 and either determined from
  - Compressional tests on core plug samples which known as static Poisson's ratio (v_{st}) or
  - Derived from shear and compressional wave velocities

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10

Determination of Geomechanical Parameters

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- Since retrieving core samples representing the sections of interest is very costly and requires a lot of time, core-testing data cannot yield a continuous profile for the geomechanical property along the drilled wellbore.
- Representative core samples are not always available and their number is often restricted.
- Indirect methods were developed to fill the missing gaps using derived correlations between the rock mechanical properties and well-logs.
- Many authors developed empirical correlations to estimate static elastic properties from the dynamic properties.

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Determination of Geomechanical Parameters

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Empirical correlations for Es prediction:

Author	Equation	R^2	Samples	Rock type/s
Brotons et al., 2016	$E_{st} = 3.97E6\ \rho^{-2.09} E_{dyn}^{1.287} \emptyset^{-0.116}$	0.994	57	igneous, sedimentary and metamorphic rocks
Mahmoud et al., 2016	$\ln E_{st} = 14.846 - 0.613\ \ln(\Delta t_c) - 2.179\ \ln(\Delta t_s) + 1.418 \ln(\rho)$	0.992	+300	mostly limestone
Horsrud, 2001	$E_{st} = 0.076\ V_P^{3.23}$	0.99	14	shale
Brotons et al., 2014	$E_{st} = 0.867\ E_{dyn} - 2.085$	0.96	24	Calcarenite stone
Najibi et al., 2015	$E_{st} = 0.014\ E_{dyn}^{1.96}$	0.9	45	limestone
Canady, 2011	$E_{st} = \frac{\ln(E_{dyn} + 1) * (E_{dyn} - 2)}{4.5}$	NA	NA	NA
Ghafoori et al., 2018	$E_{st} = 0.022\ E_{dyn}^{1.774}$	0.912	60	limestone rocks
Asef and Farrokhrouz, 2017	$E_{st} = E_{dyn}(1 - \emptyset) - 3 \ln \emptyset$	0.92	+ 100	limestone, sandstone, shale, and tuff
Feng et al., 2019	$E_{st} = 0.81\ E_{dyn} - 13.88$	0.92	18	Tight sandstone, siltstone

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Determination of Geomechanical Parameters

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Empirical correlations for static Poisson's ratio prediction:

Authors	Equation	R^2	Samples	Rock type/s
Christaras et al., 1994	$\nu_{st} = 0.71\ \nu_{dyn} + 0.063$	0.543	8	Limestone Gypsum Basalts Granite Phonolite Andesite
Wang et al., 2009	$\nu_{st} = a\ V_s + b$ $\nu_{st} = c\ V_p + d$ a, b ,c and d vary with rock type	0.835	+ 130	Peridotite Granite pyrite pyrrhotite
Feng et al., 2019	$\nu_{st} = a\ \nu_{dyn} - b$ a and b are different for different porosity ranges	0.92	18	Tight sandstone, siltstone

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13

Determination of Geomechanical Parameters

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- Several correlations for UCS prediction using sonic transit time (Δt) and porosity (Ø).
- Artificial intelligence has been employed to correlate the UCS with different well-log data such as bulk density and sonic log data.
- Well-log data are not always available while drilling.
- The acquisition of logging data while drilling is a costly and time-consuming process.

Correlation
$\mathrm{UCS} = \left(\frac{7682}{\Delta t}\right)^{1.82}$
$\mathrm{UCS} = 10\left(2.44 + \frac{109.14}{\Delta t}\right)$
$\mathrm{UCS} = 143.8\exp^{(6.95\phi)}$
$\mathrm{UCS} = \left(\frac{80204}{\Delta t}\right)^{1.285}$
$\mathrm{UCS} = 7600e^{-0.064\Delta t_c}$
$\mathrm{UCS} = 292.047e^{-9.541\phi}$
$\mathrm{UCS} = 570.808e^{-0.031\Delta t_c}$

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14

Artificial Intelligence Applications

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- The accuracy of empirical correlations are limited with the few core samples from specific rock types and the availability of the sonic wave velocities.
- The need for continuous geomechanical profile with high accuracy, highlights the use of Artificial Intelligence (AI) with its booming utilization in petroleum industry.
- The AI techniques become hotspot and can be utilized to perform analysis of huge data and trends interpretation in least time and effort with less cost and errors.
- Due to its high performance, AI provided a robust tool for solving many operational and technical problems such as prediction of reservoir fluid and rock properties and optimization of drilling operations.

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Artificial Intelligence (AI)

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- It is defined as "the study and design of intelligent agents" which can make the machines learn from experience and perform human-like tasks.

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Artificial Intelligence Tools

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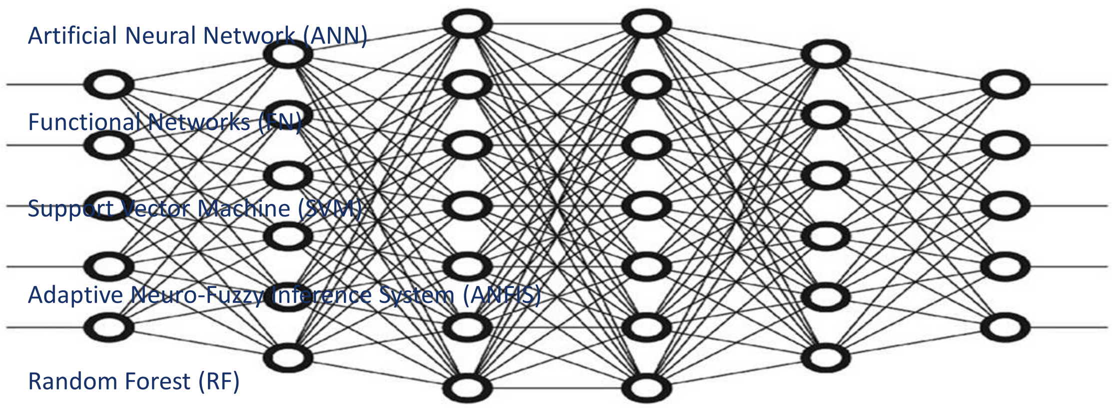
- Artificial Neural Network (ANN)
- Functional Networks (FN)
- Support Vector Machine (SVM)
- Adaptive Neuro-Fuzzy Inference System (ANFIS)
- Random Forest (RF)



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Artificial Neural Networks (ANN)

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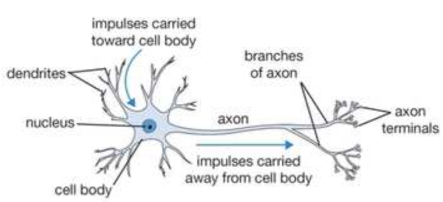
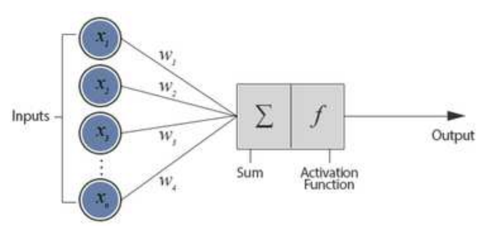
- It mimics the human biological neural networks to learn and make decisions.





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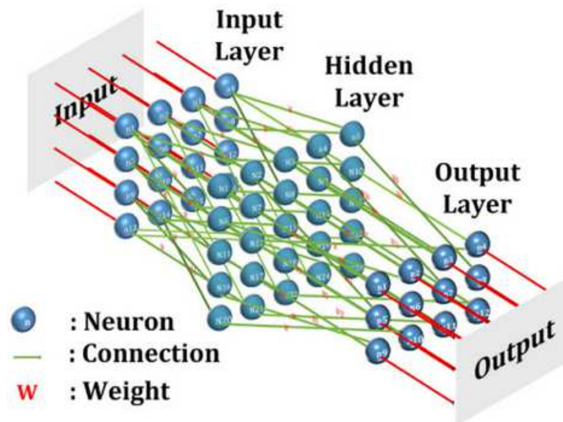
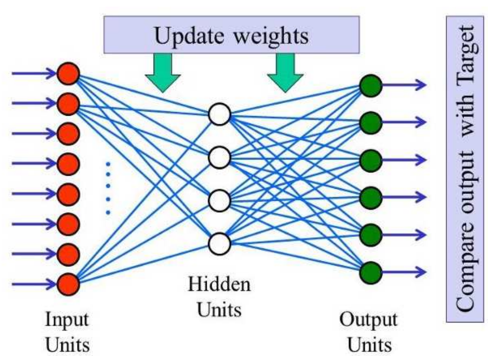
Artificial Neural Networks (ANN)

- The elementary units are neurons
- Three types of layers:
  - Input layer,
  - Hidden layer(s)
  - Output layer
- Weighted connections between layers



How ANN Works?

- Training the network with data.
- Comparing the results with actual values of the target.
- Estimate the error.
- Updating weights and biases based on the error.



Adaptive Neuro-fuzzy Inference System (ANFIS)

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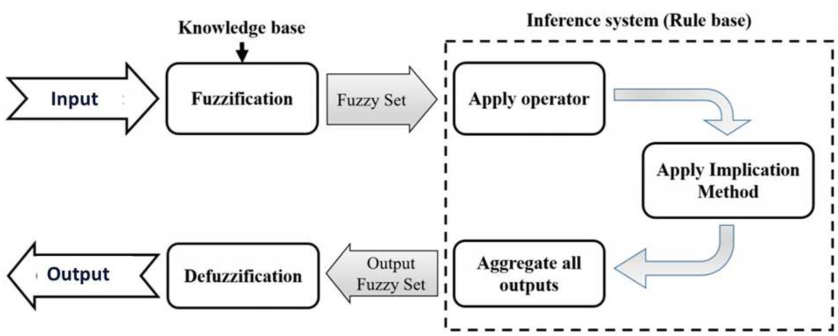
- It combines the concepts of Fuzzy logic and Neural network to form a hybrid intelligent system that enhances the ability to automatically learn and adapt.



Support Vector Machine (SVM)

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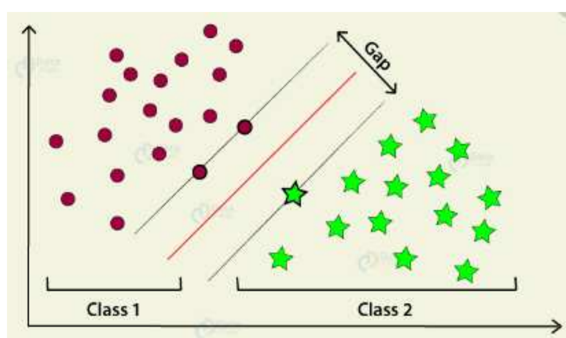
- It is a supervised learning approach that carries out transformation of an input dataset into a higher-degree dimensional "n-dimensional" feature-space whereby more space would be available for training instances the optimal hyper-plane



Functional Networks (FN)

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- It is recently introduced as a powerful predictive tool and a strong competitor with ANN for prediction- and classification-based engineering problems.
- The functions associated with each neuron use generalized functional models for processing and learning from the data obtained.
- Unlike common sigmodal forms in ANN; however, they keep adapting and changing during the learning process, depending on the nature of the dataset used.
- FN use these multi-argument functional models, so they do not need weights to be assigned to the neurons' connections (unlike neural networks) because the weights inherently exist within these neuron functions

Random Forest (RF)

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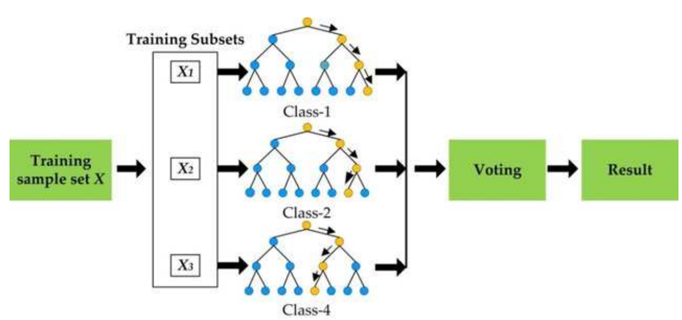
- It is a learning method for classification, regression and other tasks that operates by constructing a multitude of decision trees at training time and outputting the class that is the mode of the classes (classification) or mean/average prediction (regression) of the individual trees.



AI Work

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- Drilling engineering and machine learning research groups in CPG-KFUPM launched several projects for utilizing the AI in rock properties prediction
- The projects covers:

Prediction of	from
Logging Parameters	Logging Parameters
Geomechanical Parameters	Logging Parameters
Logging Parameters	Drilling Parameters
Geomechanical Parameters	Drilling Parameters


Springer Link

Original Article | Published: 01 January 2021

Unconfined compressive strength (UCS) prediction in real-time while drilling using artificial intelligence tools

Ahmed Gowida, Salaheldin Elkatatny & Hany Gamal

Neural Computing and Applications (2021) | Cite this article

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25

Case Study

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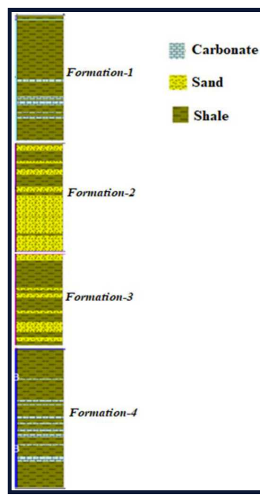
- Two wells data have been used to study the prediction of geomechanical properties from drilling parameters using AI.
- The lithology of both wells contain sandstone, shale and carbonate.
- Data from core tests, well logs and drilling parameters have been gathered.



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26

Geomechanical Parameters Studied

- Static Young's Modulus
- Dynamic Young's Modulus
- Static Poisson's Ratio
- Dynamic Poisson's Ratio

27

Why Drilling Parameters?

- Easily Available
- Earlier to Obtain
- No Additional Cost
- Continuous Information
- Related to Rock Properties

28

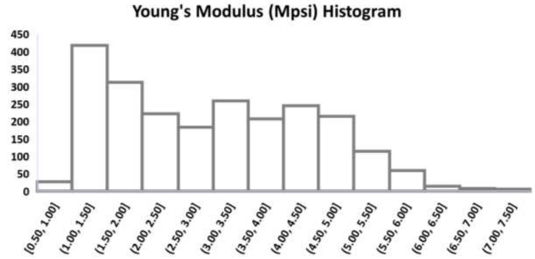
Drilling Parameters Used

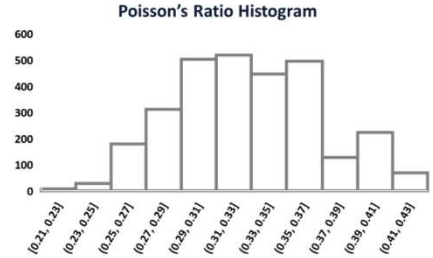
- Weight on Bit (WOB)
- Drill Pipe Torque
- Standpipe Pressure (SPP)
- Rotary Speed (RPM)
- Drilling Rate of Penetration (ROP)
- Pumping Rate (GPM)

29

Data

- 2900+ data points from Well-1 to build the models.
- 2000+ data points from well-2 to validate the developed models.





30

Workflow

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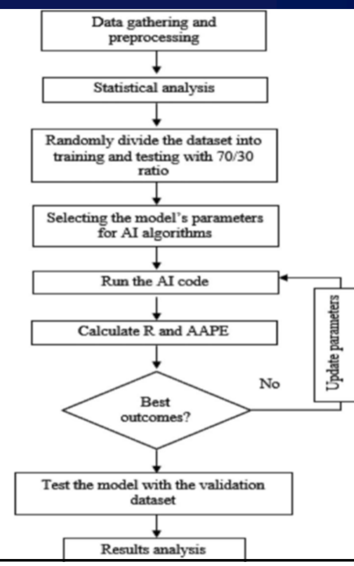
- Data collection and validation
- Smoothing and outliers removal
- Applying different ML techniques
- Sensitivity and optimization
- Validation and analysis



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Poisson's Ratio

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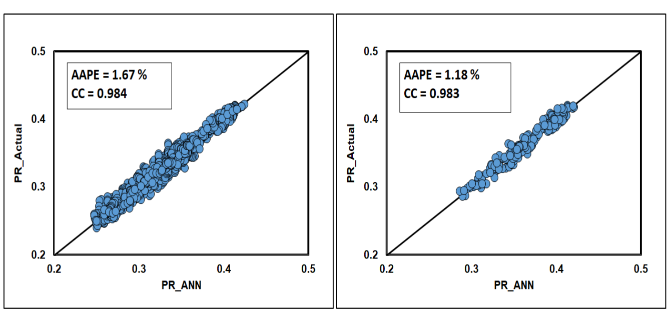

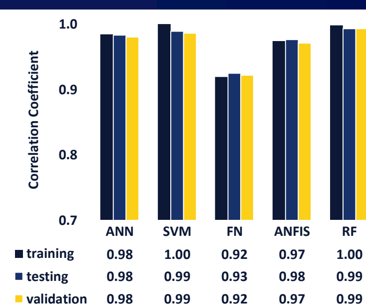

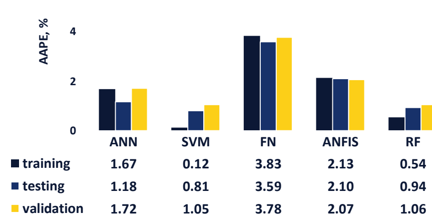

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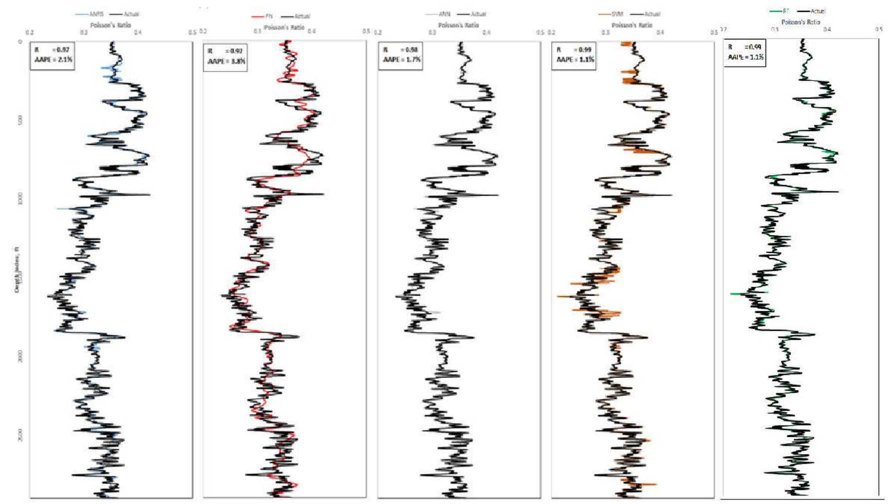
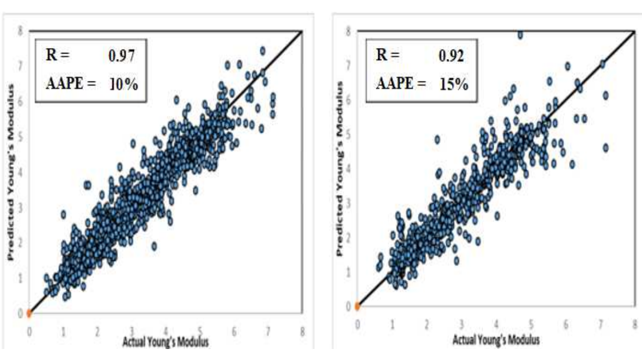
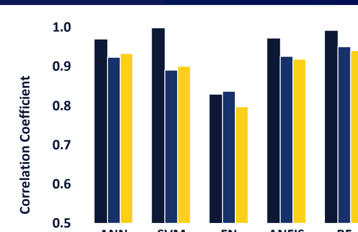
32

Validation

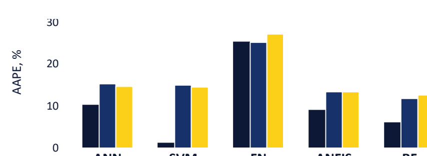


Elastic Young's Modulus



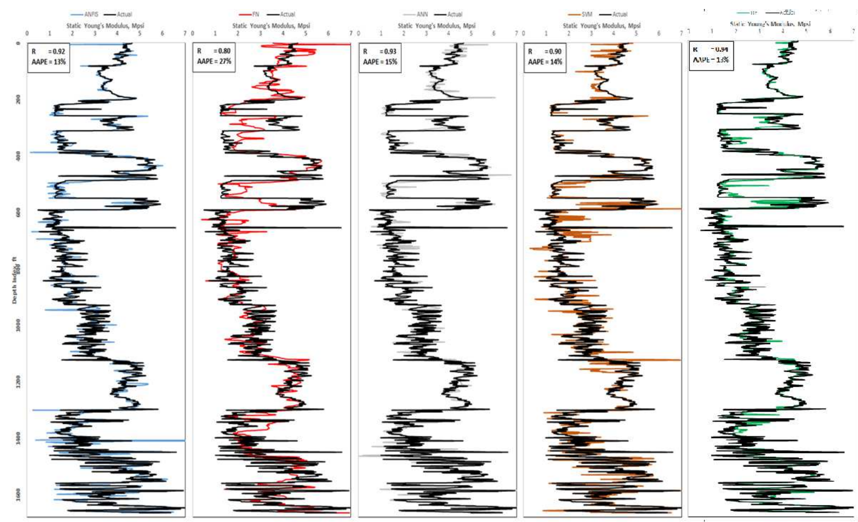


	ANN	SVM	FN	ANFIS	RF
training	0.97	1.00	0.83	0.97	0.99
testing	0.92	0.89	0.84	0.93	0.95
validation	0.93	0.90	0.80	0.92	0.94



	ANN	SVM	FN	ANFIS	RF
training	10.26	1.21	25.31	9.05	6.10
testing	15.23	14.96	25.14	13.37	11.80
validation	14.67	14.47	27.12	13.36	12.60

Validation



35

Summary

- Geomechanical properties influence wellbore stability, in-situ stresses estimation, drilling performance, and hydraulic fracturing design.
- Drilling parameters are easily available without additional cost
- Utilizing ML and drilling parameters yielded high matching accuracy between actual and estimated rock elastic parameters
- This approach develops continued real-time geomechanical profiles.

36

The Way Ahead

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- The same approach could be applied to predict other rock properties:
  - Failure Properties.
  - Unconventional Resources
  - Geothermal Application
  - Other Petrophysical Properties

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37

Recommended Papers

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RESEARCH PAPERS

Drilling Data-Based Approach to Build a Continuous Static Elastic Moduli Profile Utilizing Artificial Intelligence Techniques

Osama Mutrif Siddig , Saad Fahaid Al-Afnan , Salaheldin Mahmoud Elkatatny , Abdulazeez Abdulraheem

Check for updates

+ Author and Article Information

J. Energy Resour. Technol. Feb 2022, 144(2): 023001 (8 pages)
Paper No: JERT-21-1326 https://doi.org/10.1115/1.4050960
Published Online: May 13, 2021 Article history

Volume 2021 | Article ID 9956128 | https://doi.org/10.1155/2021/9956128

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Applications of Artificial Intelligence for Static Poisson's Ratio Prediction While Drilling

Ashraf Ahmed,[1] **Salaheldin Elkatatny**,[1] and Ahmed Alsaihati[1]

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Academic Editor: Rodolfo E. Haber

Original Paper | Published: 05 March 2021

Real-time static Poisson's ratio prediction of vertical complex lithology from drilling parameters using artificial intelligence models

Ashraf Ahmed, Salaheldin Elkatatny & Abdulazeez Abdulraheem

Arabian Journal of Geosciences **14**, Article number: 436 (2021) | Cite this article

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38

thank you!

Any questions?