Journal of Practical Information Technology

J. Prac. IT, V13, 01-11, 2022

Artificial Neural Network method and predicting lame parameter by seismic attributes

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Abstract

Geomechanical characterization is one of the significant steps in subsurface studies. Stiffness (M) and lambda parameters are two critical factors commonly used to evaluate rocks. There are some ways to masseur them which they are classified by two main methods, including direct and indirect methods. Direct methods are done on coring samples by laboratory test; however, some problems limit these methods. For example, obtaining cores in some situations is difficult or impossible. In this paper, using Deep Artificial Neural Network (DANN) based on seismic velocities, we predict stiffness and lame parameters. Finally, all results are evaluated by (R), Root Mean Square Error (RMSE), and Mean Square Error (MSE). The results prove that the DANN method should be considered a suitable tool for predicting target parameters with R=0.97 and 0.98 for stiffness and lambda parameters, respectively. Furthermore, RMSE and MSE for lame prediction are less than that of stiffness.

Keywords: Soft computing approaches, Deep learning neural network, rock stiffness, lame parameters, seismic velocities, porous media.

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1. Introduction

There are two main segments in porous media, including rock matrix and fluids. Rocks have many properties, and Stiffness (M) is one of them that plays a vital role in mechanical rock characterization [1-5]. Stiffness is taken into account as a good parameter to evaluate the deformation of rocks. In general, stiffness is an object's degree of resistance to ductility [2-3]. So the stiffness dimension is equal to the unit of force (Newtons per unit SI) divided by the unit length (meters per unit SI). Calculating stiffness in the laboratory is done by equation. 1:

$$M = \frac{F}{\delta} \tag{1}$$

Where F is the force on rock and δ is maximum deformation in rock. This point must be mentioned that there is a big difference between stiffness and hardness. As amatter of fact, hardness means the chemical hardness of a substance which is due tothe composition and chemical formula of the substance and is one of the properties and nature of a substance; But stiffness means physical hardness and does not applyto a substance but to an object or element or module; And is related to the cross- sectional shape and length of the body and other physical parameters as well as the modulus of elasticity [3, 6-8]. Since elastic parameters directly control seismic properties, in order to obtain the properties of reservoirs through seismic data, the elastic behavior of rocks must first be investigated [4]. In this way, there are some relationships between stiffness and seismic parameters:

$$M = V_P^2 \times \rho \tag{2}$$

In equation 2, M is stiffness, V_P is P–wave velocity, and ρ is density. And also, there is a relationship between stiffness and elastic modules (equation. 3):

$$M = K + \frac{4G}{3} \tag{3}$$

Where M is stiffness, K and G are bulk and shear modulus, respectively [5]. In this paper, stiffness in addition to the pressure wave velocity is estimated using the shear wave and the velocity ratio based on deep learning techniques. This is because most studies calculated stiffness utilizing laboratory measurements or experimental rock physics relationships [9-12], and intelligent methods have not paid much attention so far.

Investigating lame parameters in subsurface studies, especially in the oil and gas exploration industry, is considered an important measurement. To be more accurate, LMR (Lambda Mu Rho) analysis is an effective and widely used technique in separating reservoir fluids and lithological diagnosis [10-16]. Lambda (λ) parameter is one of the most important in reservoir geomechanics and mechanical rock analysis, which has some relationships with elastic modulus , but in this paper, we calculate the parameter using seismic based on deep learning methods.

Some researches proposes a dynamic pricing scheme for smart electricity markets to solve the problem of demand and response [17].

2. Date use

We use well–logging data obtained directly from the well in this research. Many studies proved that there is a relationship between mechanical rock properties and seismic features, especially seismic velocities. In the current study, we use seismic velocities, including P- and S velocities, V_P and V_S, respectively. Additionally, we use velocity ratio (V_P / V_S) to obtain better and more accurate results. Density is one of the significant factors in porous media that has an important role in the mechanical changes of rocks [18-20]. We use density as another important element to calculate the target parameters. Target parameters in our study are stiffness (M) and Lambda parameter (λ), which is one of the lame parameters. All used parameters have been obtained by well–logging data from an oil carbonate reservoir in the Persian Gulf (Figures 1-3).

3. Soft computing method

For over a century, the base model for neural network algorithms was presented, and in the 20th century, scientists spent their time and resources expanding this model. This algorithm describes the relationship between the input variables (features) and the output (Target) [20-22]. The structure of the Deep Artificial Neural Network is plotted in Figure 4.

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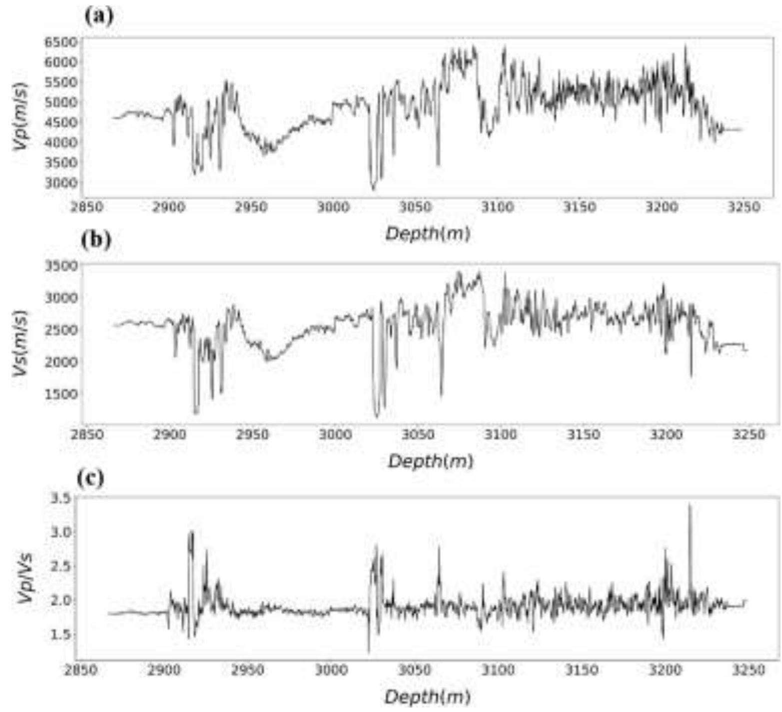

Figure 1: Seismic use data in the research (a) P- wave velocity, (b) S – wave data, and (c) velocity ratio.

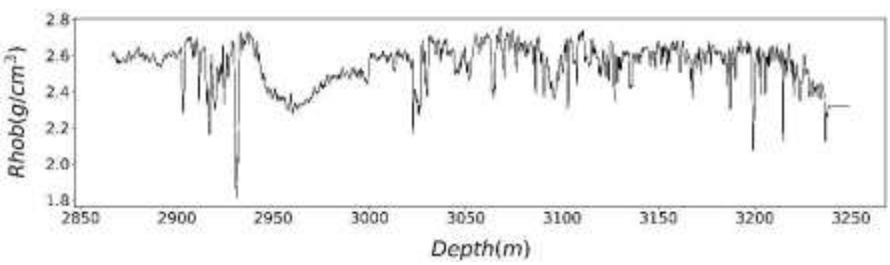

Figure 2: Density use log in the study area.

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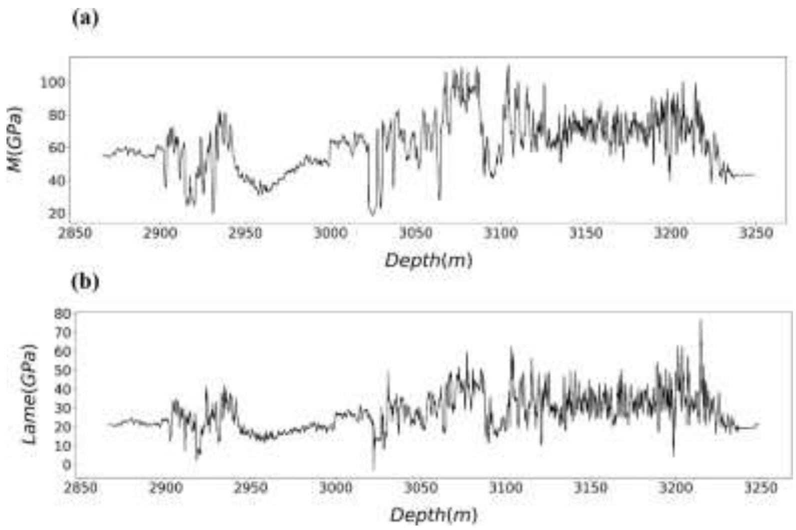

Figure 3: Seismic use data in the research (a) stiffness (M) and (b) Lame parameter

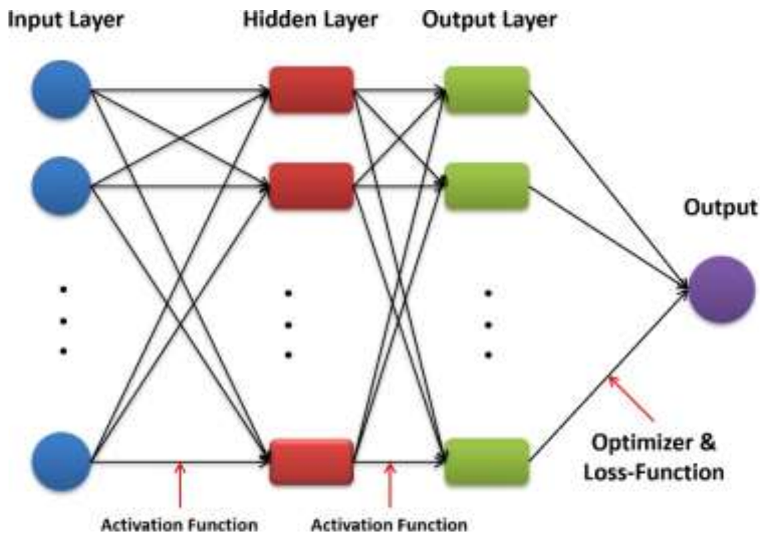

Figure 4: Deep Artificial Neural Network function.

A powerful Machine Learning tool such as ANN (Artificial Neural Network) is a complex of multiple neurons, layers, activation and loss functions, weights, and biases used for classification or regression tasks. The activation functions will differentiate the nonlinearity and linear regression methods [16]. This study uses a neural network with a hidden layer consisting of 100 neurons. Also, the activation function, loss function, and optimizer used are 'Relu,' 'Mean-Squared Error,' and 'Adam,' respectively. The data used in this study is a dataset consisting of over 2500 samples, but before using the data for the neural network, the data must be filtered. The dataset consisted of multiple NaNs (Not a Number). There are a lot of methods to filter the dataset from these values; one of them is to calculate the mean of the values and replace the NaN with it, which this method has been acquired in this paper. Also, for better and valid results, the selection method of values was put to random selection for the training dataset. For the training purpose of the model, 80% of data has been selected (as mentioned before, 'randomly'), and the remaining 20% was used for testing the model.

4. Results and discussion

The current study uses seismic velocities and density as input data for the ANN method. In the first step, the correlation between them and target parameters should be identified. Figure 5 shows the relationship between input data, stiffness, and lame parameter.

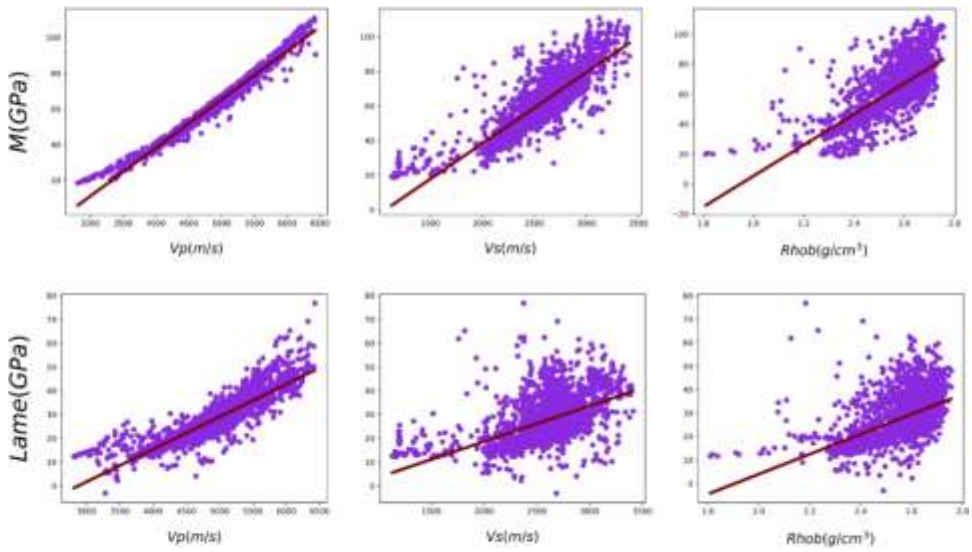

Figure 5: Correlation between seismic velocities and density as input data and desired parameters (M and lame parameter)

In general, the correlation between the input data and stiffness in the rock is greater than their correlation and the lamella parameter. Figure 5 shows that the highest correlation is related to P-wave velocity and stiffness because the higher the rock's stiffness, the less porosity and fluid content. As a result, the density of the rock is higher.

To calculate the correlation between input data and the target data, we used the Pearson correlation coefficient method, which the results are shown in the table below, Table 1. Pearson correlation coefficient is a linear correlation between two sets of data, and it is normalized between -1 and +1, as +1 would be considered the perfect correlation. This coefficient is a ratio between covariance of the two sets of data and their product of standard deviation.

Table 1: Values of Pearson Correlation Coefficient between input data and the target data

Input Data	M(GPa)	Lame (GPa)
Vp(m/s)	0.988	0.889
Vs(m/s)	0.837	0.544
Rhob(g/cm^3)	0.744	0.547

In this paper, to predict Stiffness (M) and Lame parameters of the rock, as aforementioned a neural network method consisting of 100 neurons has been utilized. As for input data, the seismic velocities, density target stiffness, and lame parameter for input data have been used. Three parameters named R-Square, RMSE, and MSE were adopted to investigate the relation between the data obtained from the ANN model and the actual data. In Figure 6, the results of the Lame parameter in three stages of the test, train, and all data for predicted data versus the actual data is plotted. In case to investigate if the ANN model functions properly and can predict the values as it should, the data will be split up into two parts of train and test, and the data selection is considered random for getting better and valid results as mentioned before. In this paper, 20% of the data was selected for testing, and as it is obvious below, a good regression exists between predicted and actual data. Table 2 shows the three correlation values between predicted and actual data of Lame (GPa).

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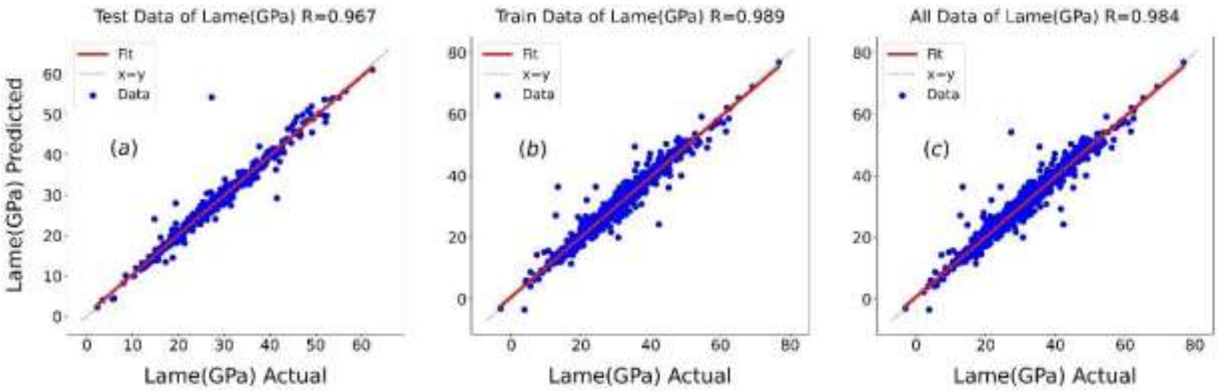

Figure 6: The results of Lame prediction by ANN method (a) Test (b) Train and (c) All data ratio.

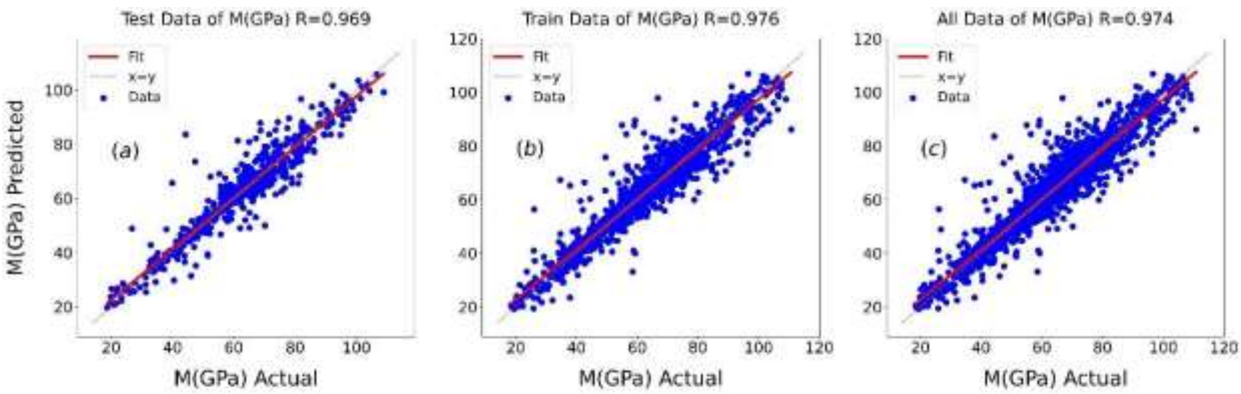

Figure 7: The results of Stiffness by ANN method (a) Test (b) Train and (c) All data ratio.

In Figure 7, the same test, train, and all data regression for predicted data versus actual data for Stiffness (M). And also, in Table 3, the correlation coefficients for data obtained from the ANN model and the actual data of Stiffness (M) are shown. From both Lame and Stiffness, it is obvious that the model has high accuracy predicted data, and it can surely predict any other data quite well.

Table 2: The prediction results of the Lame parameter by ANN method using seismic data.

Lame(GPa)	R	RMSE	MSE
Test	0.967	1.692	2.863
Train	0.989	1.666	2.776
All	0.984	1.672	2.798

Table 3: The prediction results of Stiffness by ANN method using seismic data.

Stiffness (M)(GPa)	R	RMSE	MSE
Test	0.969	5.195	26.991
Train	0.976	4.777	22.827
All	0.974	4.884	23.856

It is crucial to understand the model precision better, draw the target (actual) data, and compare it with predicted data. Figure 8 shows the perfect correlation between these two, and it states that the model can predict any data with high accuracy.

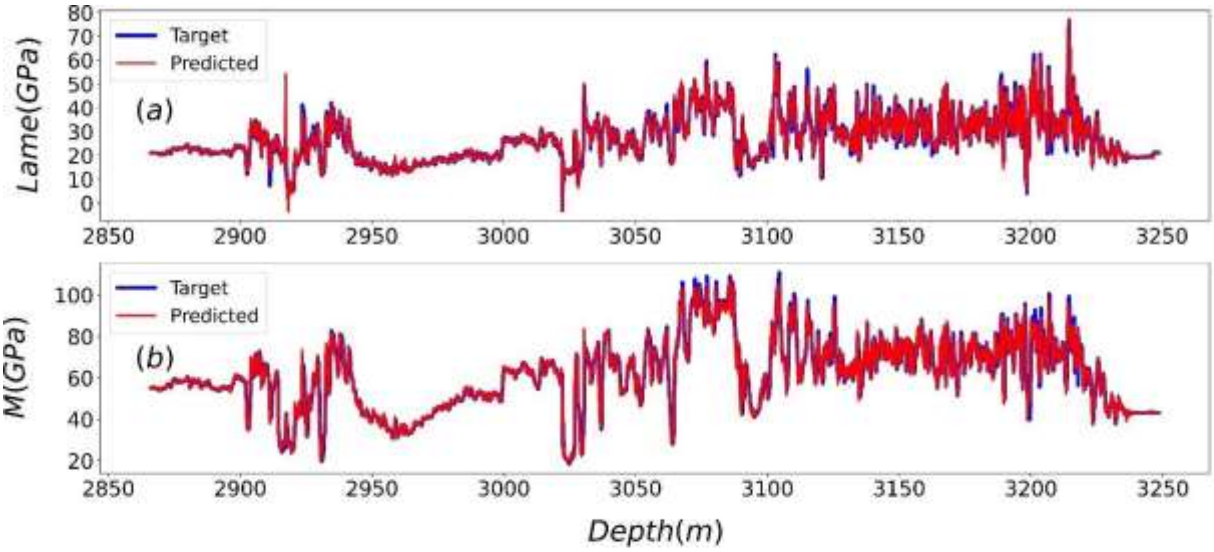

Figure 8: Target and Predicted data comparing to each other versus Depth (m) for (a) Lame (GPa) and (b) M(GPa)

5. Conclusion

The intelligent case study predicted stiffness and lame parameter using an artificial neural network technique. We utilized seismic velocities logs, P–wave and S–wave velocities to calculate in our research. The results show that the ANN could estimate the target parameters with R = 0.97 and R = 0.98 for stiffness and lame parameters; therefore, the used method can be reliable in the research area for calculating M and lame parameters.

References

[1] BADAKHSHAN, Ehsan, et al. Application of Particle Stiffness Fabric Tensor for Modeling Inherent Anisotropy in Rocks. Rock Mechanics and Rock Engineering, 2021, 1-17.

[2] XIE, Heping, et al. Experimental study on rock mechanical behavior retaining the in situ geological conditions at different depths. International Journal of Rock Mechanics and Mining Sciences, 2021, 138: 104548.

[3] BULUT, Berrak, et al. Determination of matrix composition for diamond cutting tools according to the hardness and abrasivity properties of rocks to be cut. International Journal of Refractory Metals and Hard Materials, 2021, 95: 105466.

[4] MA, Shaosen; CHEN, Weizhong; ZHAO, Wusheng. Mechanical properties and associated seismic isolation effects of foamed concrete layer in rock tunnel. *Journal of Rock Mechanics and Geotechnical Engineering*, 2019, 11.1: 159-171.

[5] Zoback, M. D. (2010). Reservoir geomechanics. Cambridge university press.

[6] GAO, Mei-ben, et al. Identifying crack initiation stress threshold in brittle rocks using axial strain stiffness characteristics. Journal of Mountain Science, 2018, 15.6: 1371-1382.

[7] HUNZIKER, Jürg, et al. Seismic attenuation and stiffness modulus dispersion in porous rocks containing stochastic fracture networks. Journal of Geophysical Research: Solid Earth, 2018, 123.1: 125-143.

[8] GORDIN, Y., et al. Rock Physics Application for Predicting Thermal Maturation of Organic-Rich Carbonates. In: 55th US Rock Mechanics/Geomechanics Symposium. OnePetro, 2021.

[9] Avseth, P., & Veggeland, T. Seismic screening of rock stiffness and fluid softening using rock-physics attributes. Interpretation, 3(4), SAE85-SAE93, 2015.

[10] Arabali, A., Khajehzadeh, M., Keawsawasvong, S., Mohammed, A. H., & Khan, B. (2022). An Adaptive Tunicate Swarm Algorithm for Optimization of Shallow Foundation. IEEE Access, 10, 39204-39219. doi:10.1109/ACCESS.2022.3164734

[11] Asgari, G. R., Arabali, A., Babaei, M., & Asemi, K. (2022). Dynamic Instability of Sandwich Beams Made of Isotropic Core and Functionally Graded Graphene Platelets-Reinforced Composite Face Sheets. International Journal of Structural Stability and Dynamics, 2250092. doi:10.1142/S0219455422500924

[12] Mostofizadeh, S., & Tee, K. F. (2019). Evaluation of impact of fly ash on the improvement on type II concrete strength. Evaluation, 9, 10th.

[13] Mostofizadeh, S., & Tee, K. F. (2021). Static and Seismic Responses of Eco-Friendly Buried Concrete Pipes with Various Dosages of Fly Ash. Applied Sciences, 11(24),

11700.

[14] F Ayatollah Zadeh Shirazi, F Ebrahinifar, A Gharagozlou, Counterexamples In Chaotic Generalized Shifts, Journal of Mahani Mathematical Research Center 5 (2), 85-97

[15]Hamidreza Jalili, S. K. (2022). Recent Advances in Water Resource Engineering: Rose Publication Melbourne. https://www.amazon.com/dp/0645461288/ref=olp-opf-redir?aod=1

[16] Jalili;, A. H. D. H. (2014). Study of vortex flow extending around the reservoir sluice gate in order to increase in flushing efficiency. Iranian Water Research Journal, 08(15), 51-62.

[17] Bagherpour, R, Mozayani, N, Badnava, B. Improving demand-response scheme in smart grids using reinforcement learning. Int J Energy Res. 2021; 45(15): 21082- 21095. doi:10.1002/er.7165

[18] Sihotang, S. M., & Herawati, I. Simultaneous Seismic Inversion for Reservoir Characterization at Poseidon Field, Browse Basin, Australia. Al-Fiziya: Journal of Materials Science, Geophysics, Instrumentation and Theoretical Physics, 4(1), 63-73, 2021.

[19] Najibi, A. R., Ghafoori, M., Lashkaripour, G. R., & Asef, M. R. ,Reservoir geomechanical modeling: In-situ stress, pore pressure, and mud design. *Journal of Petroleum Science and Engineering*, *151*, 31-39, 2017.

[20] Taheri, A., RahimiZadeh, K., & Rao, R. V. (2021). An efficient Balanced Teaching-Learning-Based optimization algorithm with Individual restarting strategy for solving global optimization problems. Information Sciences, 576, 68-104.

[21] Alizadeh, S. M., Ghazanfari, A., Ehyaei, M. A., Ahmadi, A., Jamali, D. H., Nedaei, N., & Davarpanah, A. (2020). Investigation the Integration of Heliostat Solar Receiver to Gas and Combined Cycles by Energy, Exergy, and Economic Point of Views. Applied Sciences, 10(15), 5307. Retrieved from https://www.mdpi.com/2076-3417/10/15/5307

[22] Goodway, B., Szelewski, C., Overell, S., Corbett, N., & Skrypnek, T. Calibrated AVO and LMR analysis using a new DHI flat-spot AVO class 6 fluid contact to mitigate reservoir risk at Stonehouse, offshore Nova Scotia. CSEG Recorder, 33, 22-32, 2008.