Journal of Mineral Resources Engineering, 7(3): 59-75, (2022)

Imam Khomeini International University

Vol. 7, No. 3, Autumn 2022

نشریه مهندسی منابع معدنی

Journal of Mineral Resources Engineering (JMRE)

Research Paper

Introduction of Two Data-Driven Methods for Determining the Quality of Gas Facies in Western Australia

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Received: 01 Mar. 2021 **Accepted: 30 Jun. 2021**

Abstract: In determining the optimal points of production drilling, it is important to identify areas of suitable reservoir quality. For this purpose, the use of geochemical data, which is usually small in number, is common. This data discontinuity creates information gaps. If one uses more continuous data so that its modeling accuracy is suitable, the drilling could be then performed with more success. In this study, seismic and well logs data were used to classify the quality of gas facies by two non-parametric statistical (Parzen) and supervised deep learning techniques (long-term short-term memory network (LSTM)). The LSTM network was then also optimized by two heuristic optimization methods (Imperialistic competition algorithm and Whale algorithm). The obtained results indicate that both methods produce good results in classification so that the modeling accuracy of gas facies quality using supervised deep learning technique (87%) is more than that of the non-parametric Parzen (83%) method. Moreover, the application of optimization algorithms has increased the classification accuracy. The best accuracy is related to the LSTM network optimized with the imperialistic competition algorithm (90%). Geochemical reports and well cores data show the high validity of these models.

Keywords: Quality of gas facies, LSTM network, Parzen, Imperialistic competition algorithm, Whale optimization algorithm.

How to cite this article
Asgari Nezhad, Y., and Moradzadeh, A. (2022). *"Introduction of Two Data-Driven Methods for Determining the Quality of Gas Facies in Western Australia"*. Journal of Mineral Resources Engineering, 7(3): 59-75.
DOI: 10.30479/JMRE.2021.15158.1495

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INTRODUCTION

Due to the lack of geochemical data in hydrocarbon fields, the idea of using other exploration data to model geochemical parameters was proposed. Because of the complexity of unconventional gas reservoirs, the main pattern of TOC estimation, which is based on simple or multivariate regression fitting, has been replaced by intelligent methods using seismic data in recent years [1-4]. In this study, the main purpose is to model gas quality directly using acoustic impedance of seismic data and petrophysical logs using Parzen classifier and supervised deep learning algorithm (LSTM network) for the first time. Finally, the ability of LSTM network has been improved by two methods of imperialist competition algorithm (ICA) and whale algorithm (WOA).

MATERIALS AND METHODS

In this paper, two methods of Parzen and LSTM neural network are used to classify the quality of gas facies with acoustic impedance of two dimensional (2D) seismic data and well petrophysical logs. As well, the Whale and Imperialist competition algorithms have then used for optimization. They are described briefly:

Parzen classifier

In the Parzen classifier, the probability of each data belonging to each class is investigated by computing the probability density function (Equation 1).

$$P_n(x) = \frac{1}{n}\sum_{i=1}^{n}\frac{1}{h_n}\varphi\left(\frac{x - x_i}{h_n}\right) \tag{1}$$

Where:

P_n (x): a function for the parzen window with center x and radius of h_n

n: The number of data

x_i: is the data being studied (i = 1,2,…, n) [5].

LSTM Network

The LSTM networks have a sequence structure, but its main difference with the recurrent neural network is that LSTM networks have four layers in each hidden layer (Figure 1). The key point in LSTMs is the cell state, the horizontal line running through the top of the diagram. The cell state is like a conveyor belt. The LSTM does have the ability to remove or add information to the cell state, carefully regulated by structures called gates. Gates are a way to optionally let information through. They are composed out of a sigmoid neural net layer and a pointwise multiplication operation [6].

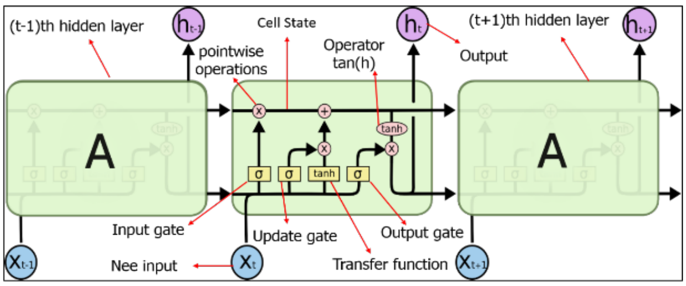


Figure 1. Duplicate units in the LSTM network with three hidden layers (each large rectangles) in each of them four layers interact with each other [6]

Imperialist Competition Optimization Algorithm

The ICA is a method in the field of evolutionary computing that finds the optimal answers to various optimization problems. The steps for performing this method are shown in Figure 2.

Whale optimization algorithm

This algorithm (WOA) is one of the heuristic optimization methods. The basis of the WOA is how to hunt humpback whales. A summary of the operation of the whale algorithm is as follows [8]:

1 .Create an initial population
2 .Calculate the suitability of each search factor
3 .Get the best initial search agent
4 .Update the current search agent position
5 .If maximum repetition is reached: End
6. Otherwise refer to step 2

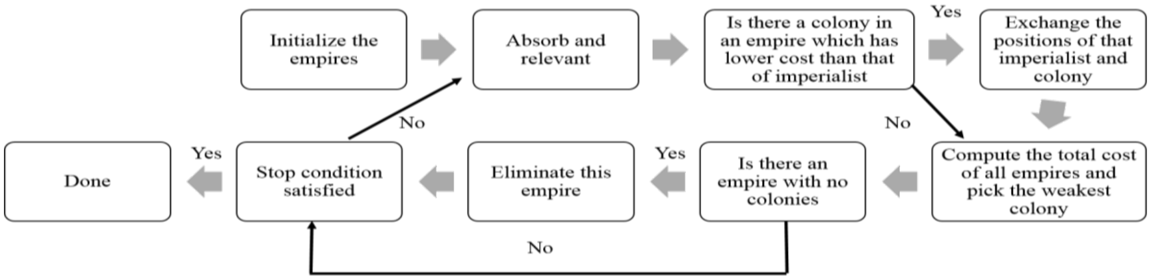


Figure 2. The steps of pseudo code for imperialist competition optimization algorithm [7]

RESULTS AND DISCUSSION

Modeling results of the Parzen classifier

The results of classification of good quality and bad quality facies by the Parzen method for the acoustic impedance of 2D seismic data can be seen in Figure 3A. It is seen that the Parzen modeling has acceptable accuracy, but at some depths (such as 1285 meters) some interlayers are appeared.

Modeling results of the LSTM

The gateways in the network work with the common sigmoid function to send the data to the next stage based on spatial sequences. The hyperbolic tangent function is used to transfer information from the gates to the state cell. The number of optimal hidden layers (obtained by repetition) was selected equal to 8. The modeling results are shown in Figure 3B. Some of the noise and interlayers that were present in the Parzen model have been removed in this model, and the boundaries of the layers are well separated from each other, except at a depth of 1380 meters.

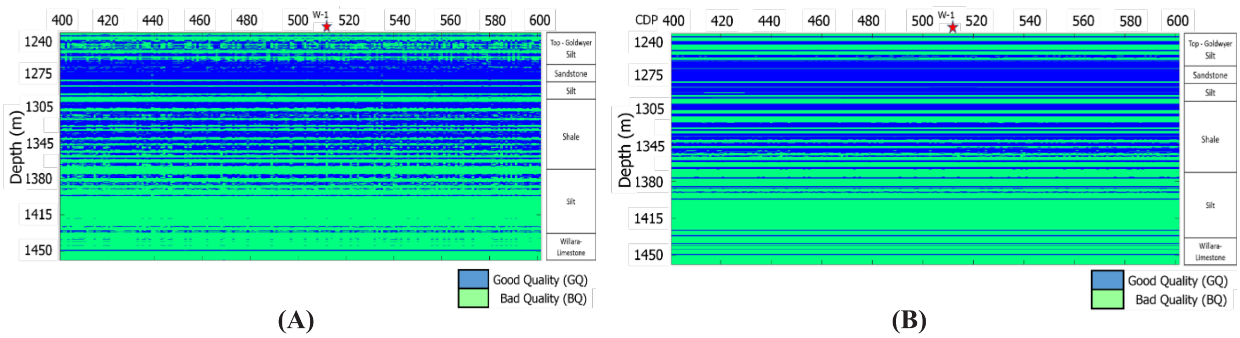


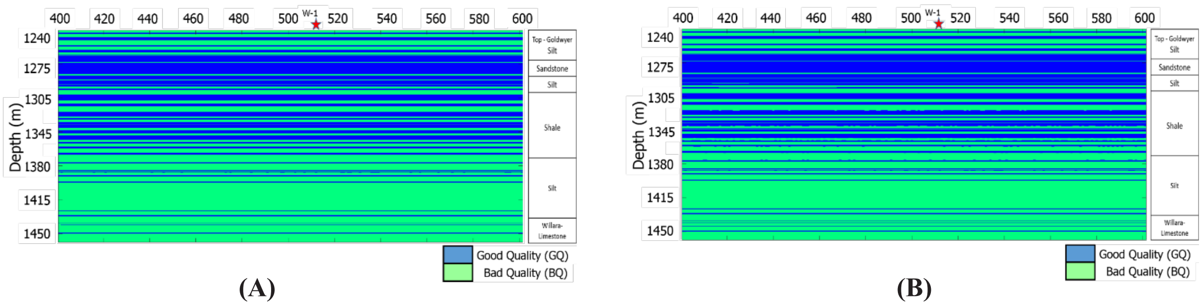
Figure 3. Two-dimensional cross section of the result of classification of gas facies quality along seismic profile with W-1 well using **A:** Parzen classifier and **B:** Supervised LSTM

Modeling with optimized LSTM network with ICA

The results of this optimized network for facies classification are shown in Figure 4A. As seen, the noise and interlayers in shale and silt layers have been disappeared. In other words, with the ICA optimized model, the complexities of the reservoir are well identified.

Modeling with optimized LSTM network with WOA

The second algorithm used to optimize the LSTM network was the whale algorithm. Figure 4B shows the model optimized by this algorithm. The WOA optimized model properly identifies the layer boundaries. Moreover, in this model, the noise in the main model has been reduced sufficiently.



(A) **(B)**

Figure 4. Two-dimensional cross section of the result of classification of gas facies quality along seismic profile with W-1 well using optimized LSTM by **A:** ICA and **B:** WOA

The modelling accuracy of the methods is evaluated at the well location on the profile. This is done by comparing the accuracy of the methods that provided by confusion matrix (Table 1) and visual comparison (Figure 5). The obtained results show that the accuracy of the ICA optimized LSTM network for classification and modeling of gas facies quality is (90%) better than those obtained by other methods.

Table 1. Comparison of confusion matrix and modeling accuracy with Parzen, simple and optimized LSTM network with two ICA and WOA methods

Classifiers	Confusion Matrix	Accuracy
Parzen	$\begin{bmatrix} 87.3 & 12.7 \\ 19.3 & 80.7 \end{bmatrix}$	%84
LSTM	$\begin{bmatrix} 89.2 & 10.8 \\ 15 & 85 \end{bmatrix}$	%87
Optimized LSTM by ICA	$\begin{bmatrix} 92.3 & 7.7 \\ 12.2 & 87.8 \end{bmatrix}$	%90
Optimized LSTM by WOA	$\begin{bmatrix} 91.5 & 8.5 \\ 13.4 & 86.6 \end{bmatrix}$	%89

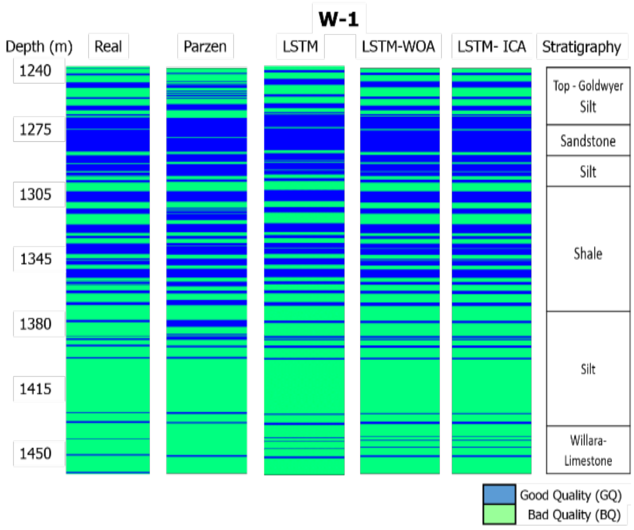


Figure 4. Image comparison between real data, Parzen classification results, simple LSTM network, LSTM network optimized by WOA and LSTM network optimized by the ICA at the well location (The right column depicts stratigraphic column of the well.)

CONCLUSION

Considering the results of modeling and examining the accuracy of each method, the following results have been obtained:

- The detection accuracy of quality zones using Parzen classifier was 84%.
- The accuracy of the proposed model using the supervised deep learning LSTM was 87%.
- The WOA has shown good performance with a 2% increase in accuracy (89%) compared to the simple LSTM network. Besides the ICA had the best performance between the two optimization algorithms in this study (90%).
- In general, the use of optimized LSTM network with ICA provided very good accuracy for classifying gas facies.

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