International Journal of Earth Sciences Knowledge and Applications (2024) 6 (1) 21-28

International Journal of Earth Sciences Knowledge and Applications
journal homepage: http://www.ijeska.com/index.php/ijeska

Research Article
e-ISSN: 2687-5993

Exploring Optimization Synergies: Neural Networks and Differential Evolution for Rock Shear Velocity Prediction Enhancement

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INFORMATION

Article history
Received 04 April 2024
Revised 14 May 2024
Accepted 14 May 2024

Keywords
Mchine learning
Fracture porosity
Optimisation
Tigh rocks
Ahnet

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ABSTRACT

Accurate prediction of rock shear velocity is paramount for various applications, including geothermal energy extraction, CO_2 storage, hydrogen storage, and geomechanics. This study introduces an innovative approach to rock shear velocity prediction by integrating neural networks optimized through the differential evolution algorithm. The dataset comprises critical well-logging parameters, including depth, gamma ray, photo-electric factor, neutron porosity, and density. Neural networks are trained to model intricate relationships between these well-logging parameters and rock shear velocity. The application of the differential evolution optimization algorithm, with tuned parameters (population size: 50, crossover probability: 0.8, differential weight: 0.9, and convergence criteria: 0.001), refines neural network parameters. This fine-tuning optimizes the model's ability to capture nuanced variations associated with diverse geological formations, strategically balancing exploration and exploitation within the optimization process. Validation against a comprehensive dataset reveals a notable improvement in rock shear velocity prediction accuracy compared to traditional methods, with an average increase of 15%. Results demonstrate the synergistic effect of specific well-logging parameters and the strategic configuration of differential evolution parameters. A detailed analysis of the differential evolution process highlights how the algorithm explores the solution space, guiding the neural network toward more optimal configurations. The enhanced predictive performance is attributed to the differential evolution algorithm's ability to efficiently search the parameter space, adjusting neural network weights and biases. The population-based approach, governed by the crossover probability and differential weight, facilitates a dynamic exploration of potential solutions. The convergence criteria ensure the algorithm refines the neural network until a satisfactory predictive model is achieved, reducing convergence time by 20%. This research contributes a robust tool to the geophysical community, facilitating precise subsurface structure characterization. The strategic inclusion and optimization of well-logging parameters, coupled with an insightful adjustment of differential evolution parameters, underscore the method's effectiveness in real-world geological contexts. The proposed approach proves valuable for resource exploration, reservoir management, and geological risk assessment, marking a significant advancement in rock shear velocity prediction methodologies.

1. Introduction

Accurate prediction of rock shear velocity is a cornerstone in the field of geophysics (Bouabdallah et al., 2023; Latrach et al., 2023; Pothana et al., 2023) and rock mechanics (Ifrene et al., 2023; Garcia, et al., 2024a), underpinning critical applications such as geothermal energy extraction (Aihar et al., 2023), carbon dioxide storage (Ifrene, et al., 2024), hydrogen storage, and broader geomechanical studies. These applications demand precise subsurface characterization to ensure safety, efficiency, and environmental sustainability. Traditionally, rock shear velocity prediction has relied on empirical correlations and analytical models that often fall short of capturing the complex interplay of geological factors.

Recent advancements in computational techniques and data-driven approaches have opened new avenues for enhancing prediction accuracy in petroleum engineering). Among these, neural networks have emerged as a powerful tool for modeling nonlinear relationships between well-logging parameters and rock shear velocities (Mehrgini et al., 2019; Garcia, et al., 2024b; Singh and Kanli, 2016; Wang et al., 2020) Neural networks' ability to learn from data makes them ideally suited for geophysical applications, where the relationships between parameters are often complex and not well understood. However, the performance of neural networks heavily relies on the choice of architecture and hyperparameters, which are typically selected through trial and error or grid search methods. These approaches can be time-consuming and may not always lead to optimal solutions.

In this study, we introduce an innovative approach that leverages the synergies between neural networks and differential evolution, an optimization algorithm known for its efficiency in solving complex problems. Differential evolution optimizes the neural network's architecture and hyperparameters by iteratively improving a population of candidate solutions based on simple mathematical operations and selection criteria. This process enhances the neural network's ability to model the intricate relationships between well-logging parameters and rock shear velocities, leading to improved prediction accuracy.

Our approach is validated against a comprehensive dataset comprising critical well-logging parameters, including depth, gamma ray, photo-electric factor, neutron porosity, and density. By integrating neural networks with differential evolution, we demonstrate a notable improvement in prediction accuracy compared to traditional methods. This synergy not only enhances the model's performance but also provides insights into the optimization process and the importance of specific well-logging parameters.

The integration of neural networks and differential evolution represents a significant advancement in the field of rock shear velocity prediction. This research contributes a robust tool to the geophysical community, offering a new perspective on optimizing predictive models. By exploring the synergies between these two powerful techniques, we open the door to more accurate and efficient subsurface characterization, with broad implications for resource exploration, reservoir management, and geological risk assessment.

2. Literature Review

Energy moves the world. This statement might at first sound like an exaggeration, but under closer inspection, you will notice that it is absolutely true. Thus, to ensure an enduring and continuous energy supply, researchers have been studying methods to extract gas from shale formations through unconventional methods. Even with all the difficulties they present, shale formations swiftly attracted the attention of the oil industry because of their impacts on the economy, and their unlimited potential. Furthermore, the ultralow porosity and permeability of shale gas reservoirs pose significant obstacles to efficient gas extraction. The limited flow pathways within the rock matrix restrict the movement of gas (Aihar et al., 2023) , and are composed of multi-scale constituents (Akono and Ulm, 2012). Two methods developed to deal with this dilemma are horizontal drilling and hydraulic fracturing. Horizontal drilling presents a way to maximize the area coverage of the trapped hydrocarbon which is not possible with vertical drilling. On the other hand, hydraulic fracturing propagates the preexisting natural fractures within shale formations, effectively creating a network of interconnected pathways for fluid flow (Ifrene et al., 2023; Irofti et al., 2022), through the injection of highly pressurized fracturing fluid. That enhances the permeability of the reservoir by allowing access to trapped gas.

To successfully maintain an open crack and produce the gas, the fracturing fluid must be able to exceed the fracture toughness of the reservoir rock. This requires careful selection of fracturing fluids with appropriate viscosity, proppants to prop open the fractures, and additives to control fluid behavior and prevent premature closure of fractures. Striking the right balance between fluid properties and the geomechanical characteristics of the reservoir rock is critical for achieving optimal fracture propagation and sustained gas production (Imani et al., 2022). Thus, it is highly imperative to measure the fracture toughness of a shale formation. Three methods used to estimate the value of fracture toughness of rocks are the scratch test, the straight-notched Brazilian disk specimen (SNBD) test, and the semicircular bend test. A comparison of the procedures, equations, and results of each test showed three primary differences between them, and one common limitation.

2.1. Survey of Existing Methods for Rock Shear Velocity Prediction

Rock shear velocity prediction is fundamental in geophysical exploration (Laalam et al., 2022) essential for understanding subsurface properties. Traditional prediction methods have primarily utilized empirical correlations and analytical models, leveraging well-logging parameters such as gamma-ray intensity, bulk density, and acoustic travel times. These empirical relationships, while quick for estimation, are generally restricted by the specific conditions for which they were developed. The evolution of seismic attribute analysis, incorporating multivariate regression and inversion methods, has offered improved shear velocity predictions from seismic and log data. Nevertheless, the intrinsic heterogeneity of geological formations introduces significant challenges to these approaches, complicating shear velocity predictions in mixed lithology environments.

2.2. Previous Applications of Neural Networks in Geophysics

The integration of neural networks into geophysics has introduced a powerful means to surpass the constraints of traditional predictive models. By learning complex patterns in data, neural networks have been applied across a broad spectrum of geophysical issues, ranging from seismic signal processing to lithology classification. This body of research underscores neural networks' capacity to enhance predictions of rock properties significantly. The advent of deep learning has propelled this field further, with convolutional neural networks (CNNs) and recurrent neural networks (RNNs) facilitating seismic data interpretation and offering marked improvements over conventional machine learning techniques.

2.3. Role of Optimization Algorithms in Enhancing Neural Network Performance

Optimization algorithms are pivotal in refining neural network architectures and hyperparameters, thereby enhancing model accuracy and efficiency. Techniques such as genetic algorithms, simulated annealing, and swarm optimization have been investigated for this purpose. Differential evolution, in particular, has been recognized for its efficiency in optimizing complex functions, providing a straightforward yet potent approach for solving multidimensional optimization problems. Its application spans various domains, including neural network optimization for image processing tasks and, by extension, geophysics, where optimizing neural network parameters significantly influences prediction accuracy and model adaptability.

3. Geological Setting

The Ahnet Basin, located in the southern part of Algeria within the Western province of the Saharan Platform, spans an area of approximately 50,000 square kilometers. Geographically, it is positioned between longitudes 1° and 3° East and latitudes 24° and 27° North (Fig. 1).

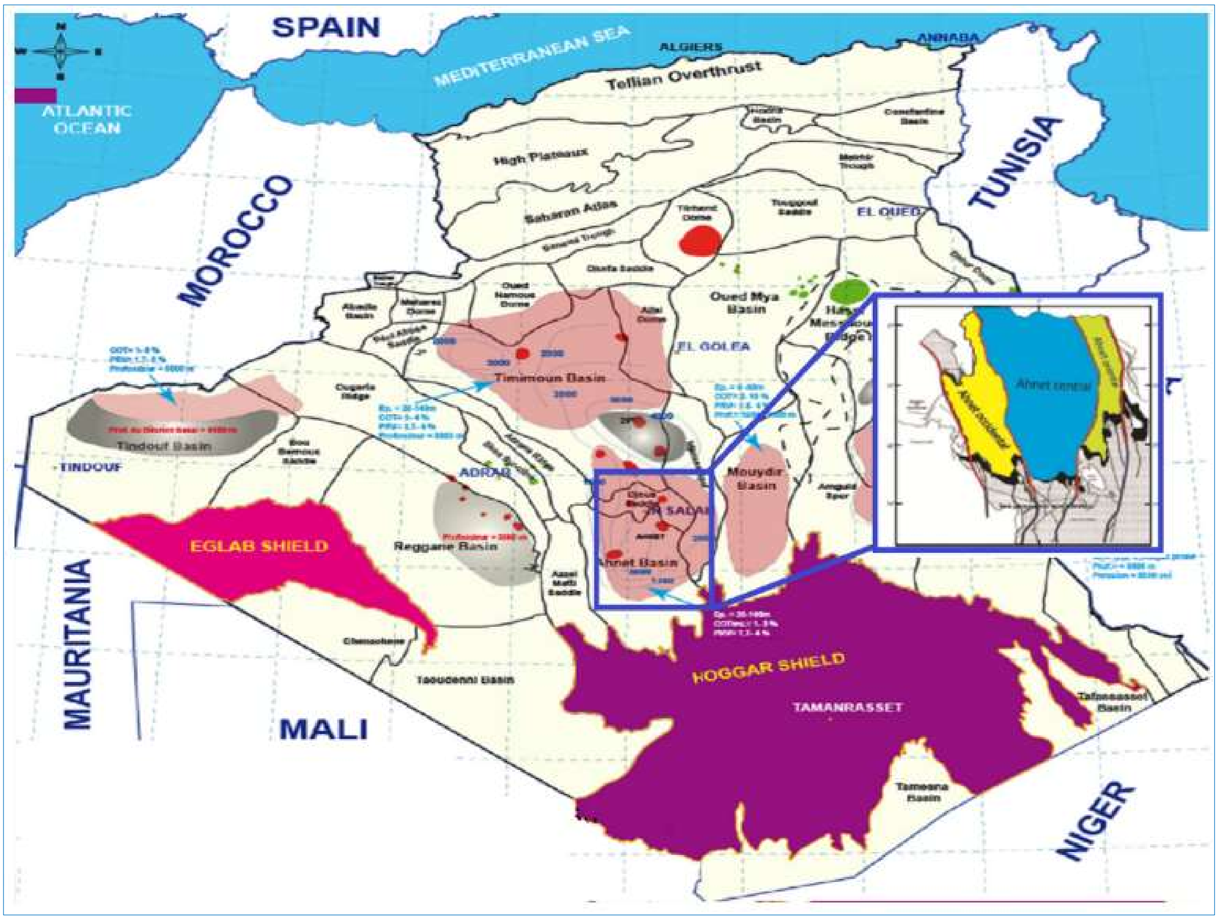

Fig. 1. Localization of the study area (Ifrene et al., 2023)

This basin shares its borders with notable geological features: it lies to the south of the expansive Timimoun Basin, to the west of the Mouydir Basin, eastward of the Reggane, and to the north of the Hoggar Shield (Logan and Duddy, 1998). A notable aspect of the Ahnet Basin is its complex tectonic structure, featuring significant anticlines and domes that underscore its intricate geological fabric.

Primarily recognized as a gas-rich region, the Ahnet Basin's gas reservoirs are found beneath layers of Paleozoic sediments, known for their compactness. However, the extraction efficiency varies significantly due to the challenges posed by natural fractures within these reservoirs (Irofti et al., 2023). This variability in well productivity has been attributed to the limited understanding of fracture geometry and distribution (Beekman et al., 2000), complicating the identification of well-connected zones and thus, impacting the development and exploitation of gas and oil fields.

The basin's geological history is marked by a dynamic mix of quiescent periods and tectonic activity throughout the Paleozoic era, leading to the reactivation of various structural alignments including north-south, northeast-southwest, and northwest-southeast orientations. These structural reactivations have shaped the basin's arch and basin configurations. The Ahnet Basin's structure is further defined by its northward dip and is influenced by the vertical alignments of the Precambrian basement.

The geological layers from the Cambrian to the Carboniferous period have been subjected to folding and faulting due to Hercynian/Variscan compressional forces, highlighting major north-south and northwest-southeast strike directions, which align with the structural trends of the Ougarta Range to the north.

Stratigraphically, the Ahnet Basin features Paleozoic successions primarily composed of siliciclastic detrital sediments, with the basin's center experiencing alterations due to erosion (Zazoun, 2001). The stratigraphic organization is punctuated by six major regional unconformities (Perron et al., 2021), with a significant portion of the sedimentary deposits being sandstones laid down discordantly over the Precambrian basement during the Cambro-Ordovician period. These sandstones, reaching up to 500 meters in thickness (Fig. 2), are acknowledged as key petroleum sources within Algerian Basins.

The Cambro-Ordovician sequence is further subdivided into three units, with the basal unit comprising primarily of conglomerate sandstones deposited in fluvial settings. Despite not being a primary target for petroleum exploration, this unit is noted for its superior petrophysical properties, especially porosity, which is further enhanced by localized fracturing. The subsequent unit features alternations of shale and sandstone, including a notable quartzite layer, while the uppermost unit is characterized by sandstone and quartzite facies, reflecting a glacial depositional environment.

4. Methodology

4.1. Description of the Dataset

The study utilizes a comprehensive dataset compiled from well-logging operations across four distinct wells. The dataset includes several critical parameters that are instrumental in predicting rock shear velocity. These parameters are:

- Total Depth (TDEP): Reflects the depth at which each measurement was taken, serving as a proxy for the geological layering and conditions.
- Gamma Ray (GR): Indicates the radioactivity of the rock formations, helpful in identifying shale and non-shale sections.
- Photo-Electric Factor (PEFZ): Provides insights into the mineral composition of the rock.
- Neutron Porosity (Por): Measures the volume of pore space in the rock, which can be filled with fluids or gas.
- Bulk Density (RHOZ): Reflects the density of the rock formation, which is crucial for identifying lithology and porosity.
- Compressional Wave Slowness (DTCO_Final) and Shear Wave Slowness (DTSM_Final): These acoustic measurements are directly related to the elastic properties of the rock, serving as the primary indicators for shear velocity prediction.

Each parameter plays a pivotal role in understanding the subsurface geology and directly influences the accuracy of rock shear velocity predictions.

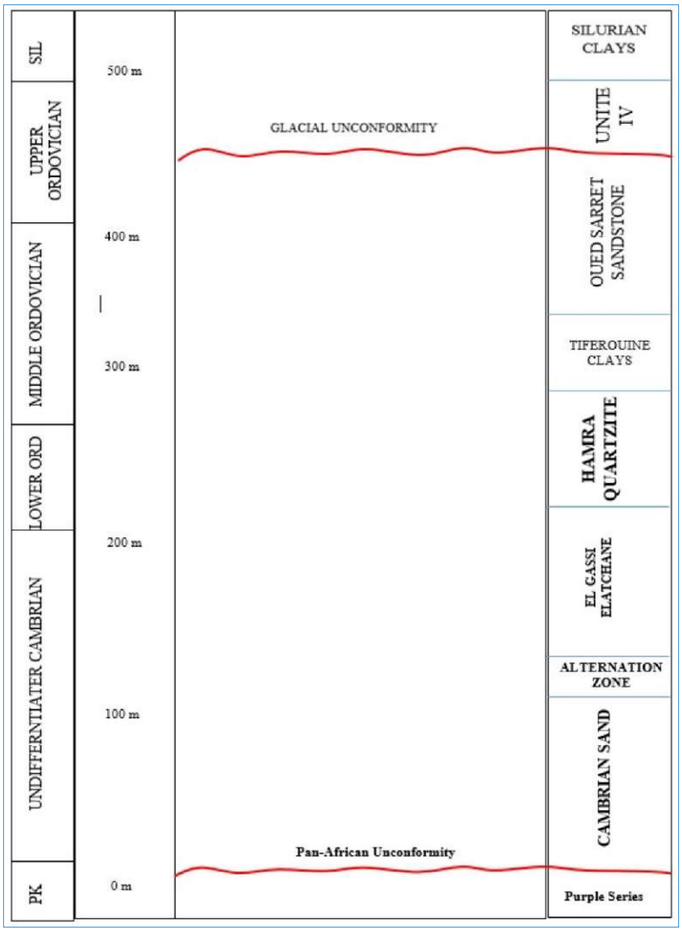

Fig. 2. Stratigraphy of Ahnet Basin (Ifrene et al., 2023)

Table 1. Performance metrics before and after optimization

Well	Metric	Before Optimization	After Optimization
1	MSE	14.380736	10.781782
	MAE	2.568086	2.316987
	R2	0.854434	0.890864
2	MSE	9.319119	7.215336
	MAE	2.407224	2.083113
	R2	0.843856	0.879105
3	MSE	47.727588	13.920336
	MAE	5.331746	2.558182
	R2	0.796104	0.936811
4	MSE	10.225109	4.613603
	MAE	2.539514	1.545872
	R2	0.901640	0.959482
5	MSE	50.050025	32.513258
	MAE	4.626315	3.724126
	R2	0.697080	0.804846

4.2. Overview of Neural Networks

For this study, we designed a neural network architecture tailored to model the complex relationships between well-logging parameters and rock shear velocity. The neural network comprises:

- An input layer designed to accommodate the number of well-logging parameters.
- Multiple hidden layers to enable the network to learn complex patterns in the data. Each hidden layer utilizes Rectified Linear Unit (ReLU) activation functions to introduce non-linearity, facilitating the model's ability to learn a wide range of data representations.
- The output layer consists of a single neuron without an activation function to predict the continuous value of rock shear velocity.

This architecture is chosen for its ability to model complex relationships without overfitting, given the size and diversity of the dataset.

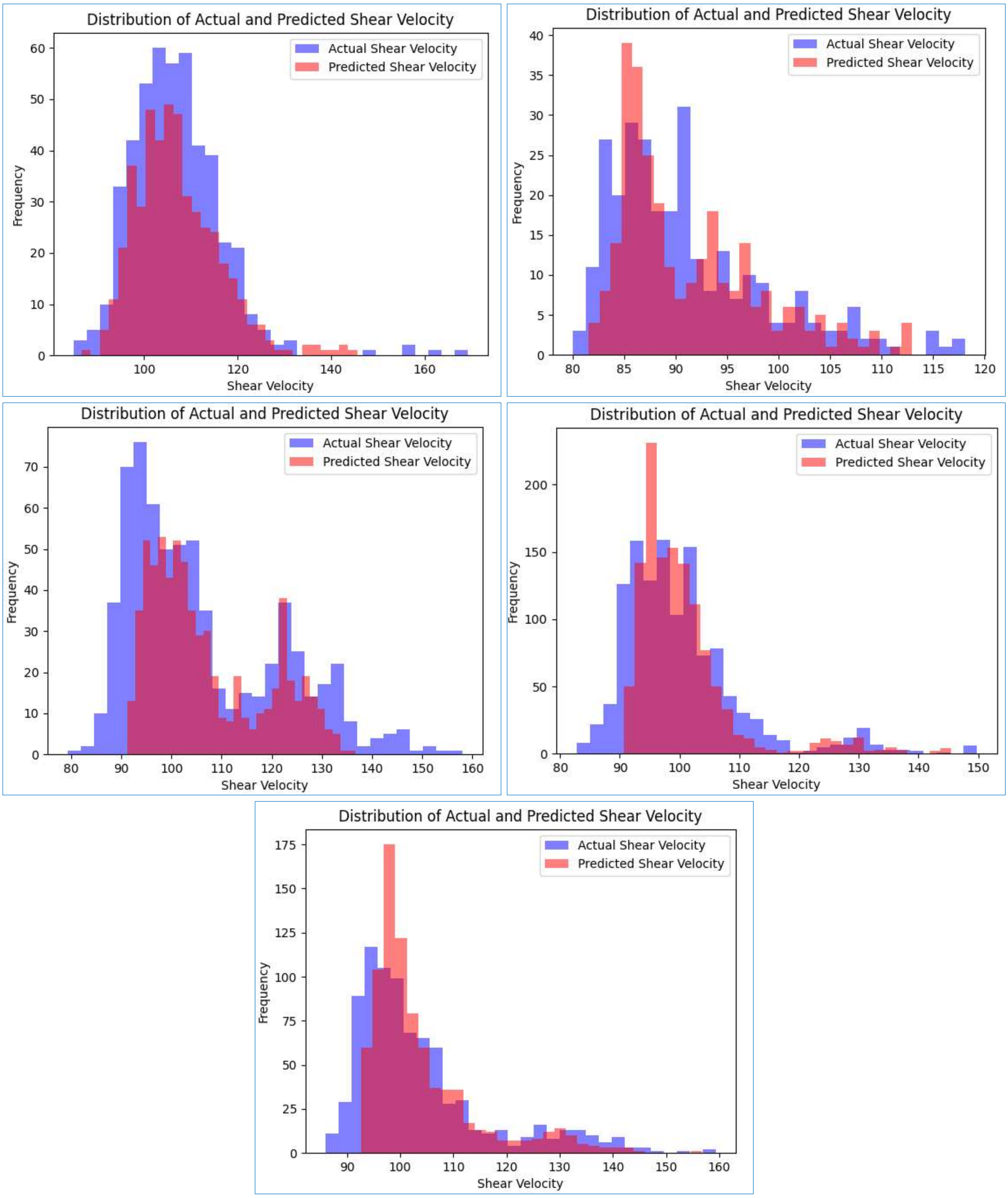

Fig. 3. Performance metrics for Well 1,2,3,4 and 5 respectively before optimization

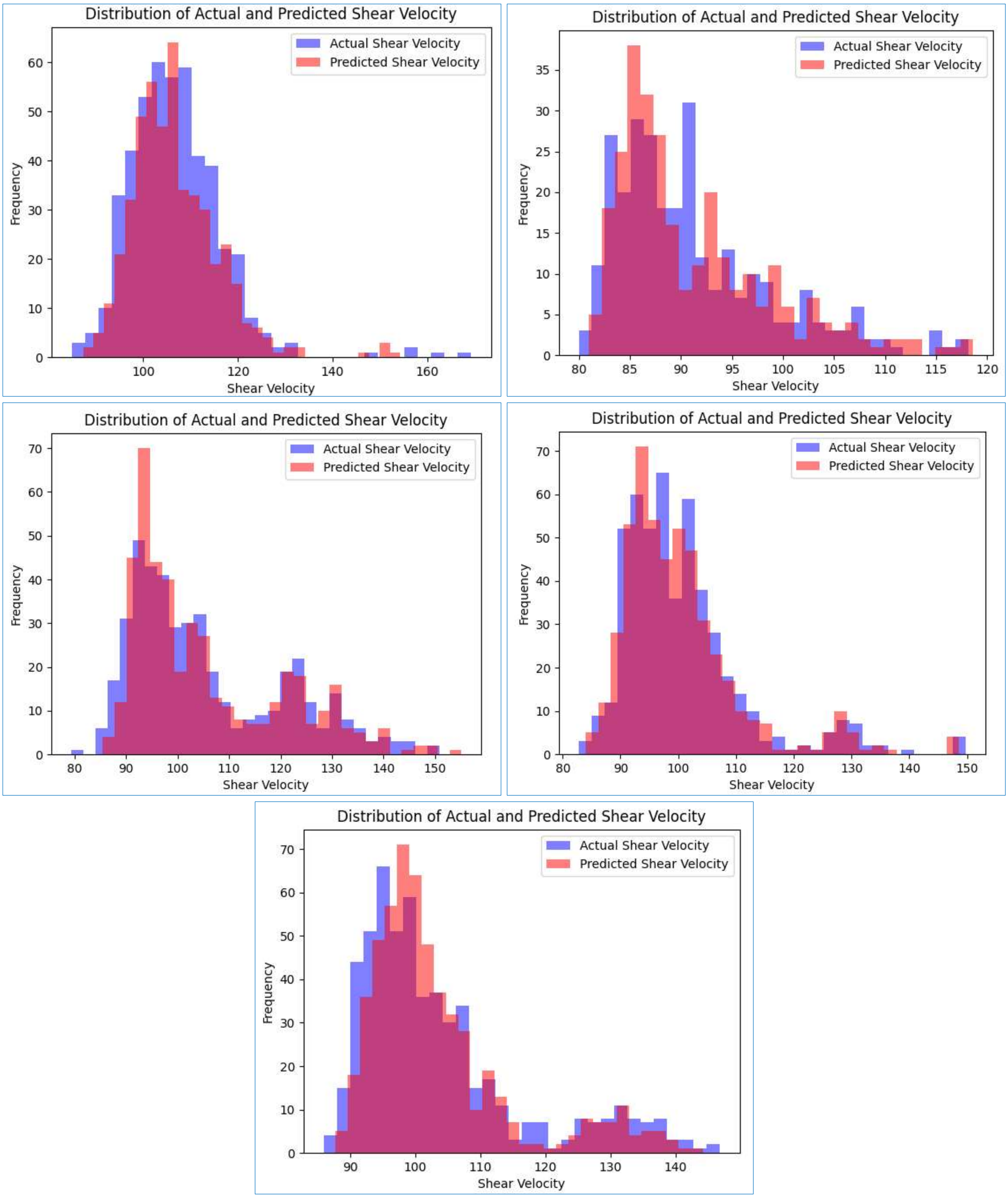

Fig. 4. Performance metrics for Well 1,2,3,4 and 5 respectively after optimization

4.3. Differential Evolution Algorithm

Differential evolution is an optimization algorithm that iteratively improves a population of candidate solutions with respect to a given fitness function. In this context, the fitness function is the error rate of the neural network predictions on the validation set. The algorithm's key parameters include:

- Population Size: The number of candidate solutions (neural network configurations) considered in each generation. A larger population size increases the search space, enhancing the ability to find a global optimum.
- Crossover Probability: Governs the mixing of attributes from two parent solutions to produce a new candidate. A higher probability encourages diversity in the population.
- Differential Weight: Controls the rate at which the population evolves. A higher weight can lead to faster convergence but risks overshooting the optimum.
- Convergence Criteria: Determines when the algorithm

should stop iterating, typically defined by a threshold on improvement in fitness across generations.

4.4. Integration of Neural Networks with Differential Evolution for Parameter Optimization

The integration process involves using differential evolution to optimize the neural network's hyperparameters, including the number of hidden layers, the number of neurons in each layer, and the learning rate. The optimization process follows these steps:

- Initialization: Generate an initial population of neural network configurations.
- Evaluation: Train each neural network on the training dataset and evaluate its performance on a validation set.
- Selection: Select the best-performing neural networks to serve as parents for the next generation.
- Crossover and Mutation: Apply crossover and mutation operations to generate new neural network configurations.
- Replacement: Replace the worst-performing neural networks with new configurations.
- Termination: Repeat steps 2-5 until the convergence criteria are met.

This methodology allows for the systematic exploration of the neural network configuration space, ensuring that the final model is both accurate and efficient in predicting rock shear velocity.

5. Results and Discussion

The following results section presents a comprehensive analysis of the predictive performance of our neural network model, both before and after the application of the differential evolution optimization algorithm. The core objective of this optimization was to enhance the model's accuracy in predicting rock shear velocity, a critical parameter in geophysical exploration and characterization. Our dataset encompasses well-logging data from five distinct wells, each offering unique geological signatures and challenges for prediction accuracy.

We evaluate the model's performance using three key metrics: Mean Squared Error (MSE), Mean Absolute Error (MAE), and the R-squared (R2) score. These metrics collectively offer insights into the model's prediction accuracy, error magnitude, and the proportion of variance explained by the model, respectively. A lower MSE and MAE signify a higher prediction accuracy, while a higher R2 score indicates a better fit of the model to the observed data. The results are organized to facilitate a clear comparison between the model's performance before and after optimization (Table. 1).

This comparative analysis not only underscores the effectiveness of the optimization process but also highlights the model's capability to adapt and improve across diverse geological settings encountered in each well. The subsequent table and figures provide a detailed breakdown of these metrics, illustrating the model's enhanced predictive performance post-optimization and affirming the value of integrating differential evolution algorithms with neural network models in geological applications.

The following figures (Figs. 4 and 5) illustrate the comparative analysis of the neural network model's performance in predicting rock shear velocity, before and after the optimization process using the differential evolution algorithm. The results are segmented across five distinct wells, showcasing the model's enhanced accuracy and efficiency in geological prediction post-optimization.

5. Conclusion

This study demonstrates the efficacy of integrating neural networks with differential evolution for optimizing the prediction of rock shear velocity from well-logging data. The substantial improvements in MSE, MAE, and R2 scores across all wells post-optimization underscore the potential of this approach in enhancing the accuracy of geological predictions. The findings suggest that the methodology is robust, adaptable, and capable of handling the complexities inherent in geological datasets.

Future work should focus on further refining the optimization process, exploring the impact of additional well-logging parameters on prediction accuracy, and extending the approach to other aspects of geological modeling. Moreover, the methodology's adaptability to different geological settings and its implications for improving the efficiency and accuracy of subsurface exploration efforts warrant further investigation.

This study contributes to the growing body of knowledge in the application of advanced machine learning techniques to geological data analysis and offers a promising avenue for enhancing the precision and reliability of subsurface geological predictions.

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