

Predicting distribution of reservoir parameters using MLFNN and CNN techniques based on seismic inversion results

Introduction

The paper proposes a practical approach to applying machine learning for distribution of shale volume and effective porosity parameters using MLFNN and CNN techniques. The research area covered the central part of the Carpathian Foreland characterised by high lithofacial variability of geological formations as well as by a complex system of paleovalleys developed in Mesozoic and Palaeozoic formations and subsequently filled with Neogene sediments. The results obtained provide a more detailed understanding of the reservoir properties of the analysed formations compared with the methods previously used, and thus lead to a better insight into the main factors and mechanisms of deposition responsible for the current facies distribution within the sedimentary basin.

Geological setting

The study area is located in southern Poland within the central part of the Carpathian Foredeep area (Figure 1). The rock formations within the area belong to four main structural stages: Neoproterozoic, Paleozoic, Permian-Mesozoic and Neogene (Figure 1).

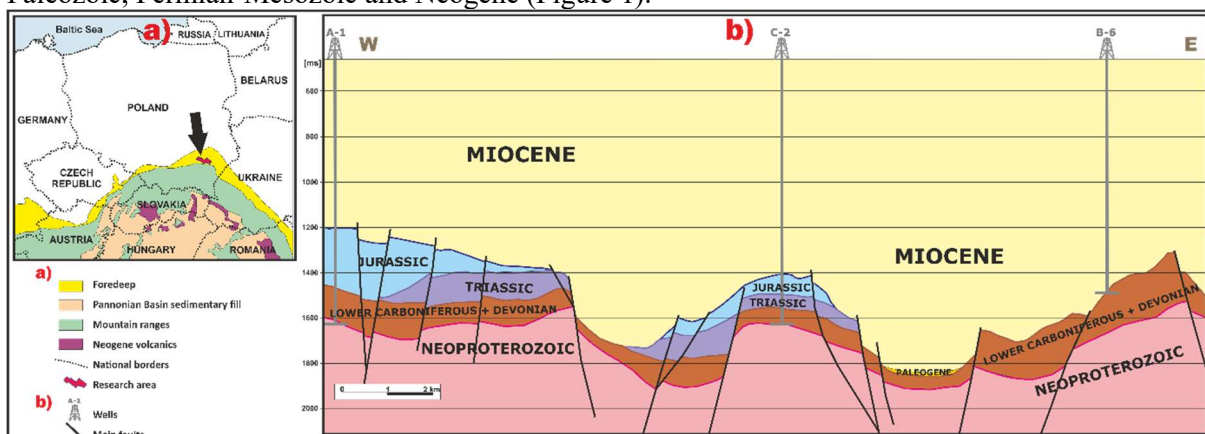


Figure 1 a) Location of the research area in the background of generalized map of the Carpathian system range, after Picha (1996) (modified); b) Generalised geological cross-section of the study area

The oldest structural stage in the research area is represented by a series of Neoproterozoic anchimetamorphic rocks. The Paleozoic stage is represented mainly by the carbonate series of Devonian and Lower Carboniferous as well as locally by the clastic deposits of Lower Carboniferous. The Mesozoic interval consists of both carbonate and clastic Triassic formations as well as the carbonate complex of Upper Jurassic-Lower Cretaceous. In the south-eastern part of the study area, Palaeogene sediments are found in the deepest parts of the palaeovalleys (Figure 2). The youngest structural stage is formed by the Miocene formations (Badenian–Sarmatian), which were initially deposited in the Carpathian Foredeep basin. The autochthonous Miocene complex can be divided into three main units: the Lower Badenian clastic sub-evaporite series, the Upper Badenian evaporite series (represented mainly by anhydrites) and the Upper Badenian–Sarmatian clastic series. There are no anhydrite sediments in the central parts of palaeovalleys, and where they are present, they have usually been redeposited here from shallower zones. The siliciclastic sediments are an essential part of the autochthonous Miocene profile and they manifest significant lithological diversity. The lower part of the profile is dominated by fine-grained deposits, mainly of the heterolithic type. In the upper part of the profile, significantly more sandstone intervals with good reservoir properties have been identified.

Methods

Seismic inversion products and well log interpretations were used for machine learning processes in this project. The seismic inversion was calculated based on deterministic simultaneous inversion method applying linearization of the classical Zoeppritz equations following the algorithms of Aki and Richards (1980). The procedure performed involved AVO/AVA inversion, which contain information derived from variations in signal amplitude depending on the angle of incidence of the seismic wave. The following elastic parameters were extracted from the seismic inversion within the framework of the project: Acoustic Impedance (AI), Shear Wave Impedance (SI), Density, MuRho ($\mu\rho$), LambdaRho ($\lambda\rho$), Vp/Vs ratio. These parameters were crucial for the machine learning processes to obtain individual models of shale volume (Vsh) and effective porosity (PHIE) in seismic cube. The models were developed utilizing well logs interpretations from 4 wells: shale volume and effective porosity logs.

A practical machine learning approach to estimate the direct reservoir parameters Vsh and PHIE across the entire volume of seismic data was employed. The machine learning was applied independently for both parameters using Multi-Layer Feed-Forward Neural Networks (MLFNN) and Convolutional Neural Networks (CNN) techniques. The MLFNN neural network, also known as a Multi-Layer Perceptron (MLP), is a classic neural network architecture that can be compared to a complex, multi-step mathematical function. In the MLFNN case, the neural network consisted of three layers: an input layer, a hidden layer, and an output layer. The input layer consisted of seismic inversion products, the hidden layer was responsible for training the network, and the output layer represented the training target PHIE or Vsh values from corresponding log. The network uses weighted learning which is optimized using a gradient combined with a backpropagation algorithm (for example Gogoi and Chatterjee 2019). In the second case, a CNN neural network was used for training, which is different to an MLFNN in that it analyzes and learns based on a small section of space, in contrast to the MLFNN, which does so point by point. The key advantage of applying CNNs to seismic data is extracting a specific feature while preserving its spatial context and relationships with the local environment. These features have a significant influence on learning in a geological context, where understanding the relationships resulting from vertical and lateral anisotropy in rock formations is essential. In this case, due to the training data, only the context of vertical variability along the well was considered. In a CNN, the convolutional layer is the most important, where filters are applied to detect and learn patterns present in the training data. Then, dimensionality reduction is used to identify the most important features from the available data, allowing the network to filter out minor noise in favor of more general trends. Finally, at the end of this process, regression is performed using a standard MLP network with a specific loss function (Li et al. 2023). The activation and loss functions were selected individually for each case in order to examine the impact of two different approaches adapted to the specific characteristics of each case.

Results

The results from machine learning using MLFNN and CNN neural networks in the two learning cases described above enable more detailed analysis of Vsh and PHIE distribution (Figures 2 and 3). Analyses conducted for various rock formations originating from different stratigraphic levels (the Palaeozoic, Mesozoic and Neogene) have revealed different ways in which they can be used to assess detailed distribution of the PHIE and Vsh parameters. The best results were obtained for the autochthonous Miocene formations, within which the variability of the parameters is represented most clearly; that may be of significant importance for understanding the nature of lithological variability and the evaluation of the reservoir characteristics of this complex. In Mesozoic and Palaeozoic carbonate formations, the distribution of the analysed parameters appears to be more homogeneous, which is mainly due to the specific characteristics of this type of rock.

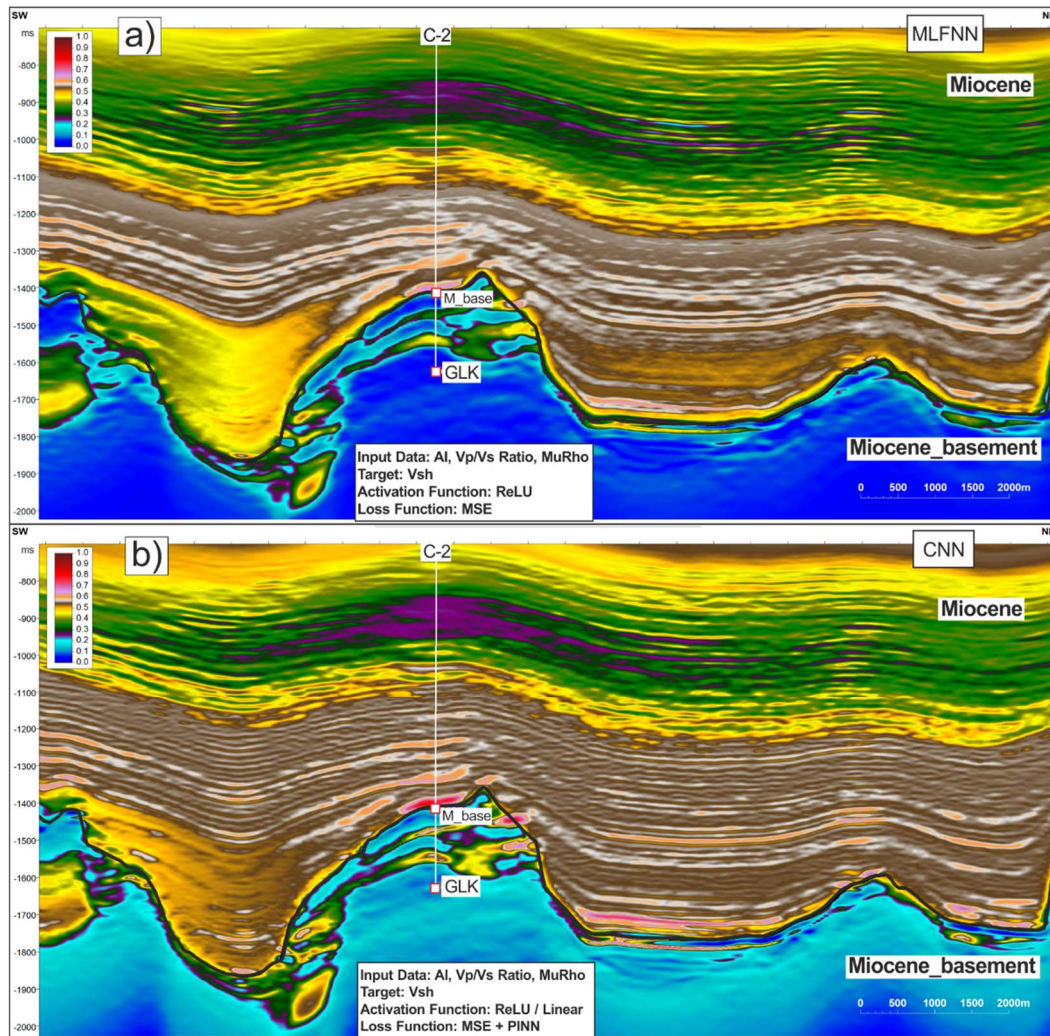


Figure 2 a) Seismic section with distribution of Vsh parameter from MLFNN; b) Seismic section with distribution of Vsh parameter from CNN

Conclusions

Figures 2 and 3 present a comparison of the results of MLFNN and CNN training methods. For the Miocene complex, the results obtained for both shale volume and effective porosity indicate a clear contrast between the series of sediments filling the paleovalleys and the formations overlying this series. Furthermore, in the deeper paleo-erosion surface, situated in the SW part of the seismic section, it could be observed that regardless of the lower Vsh parameter values, the PHIE values are similar to those observed in the formations filling the NE paleo-erosion surface. It should be noted that in both of these paleo-erosion surfaces, the sedimentary fill is of a similar nature, with a predominance of thin-bedded siliciclastic formations. Therefore, it can be assumed that the observed absence of higher PHIE values with lower Vsh results from a higher content of carbonate minerals coming from the erosion of the Mesozoic carbonate rocks surrounding the paleo-erosion surface. The upper part of the Miocene profile (above the paleo-erosion surface) clearly shows a duality regarding the diversity of the reservoir parameters analysed: the lower part consists mainly of heterolithic rocks, dominated by mudstones and characterised by low PHIE values, while the upper part contains significantly more sandstone intervals with good reservoir properties. Within the Miocene basement, carbonate rock complexes characterized by fairly homogeneous, mostly low, PHIE and Vsh values are noticeable, whereas only in their topmost part the existence of a palaeokarst surface, characterised by greater variation in the values of both parameters, can be locally detected.

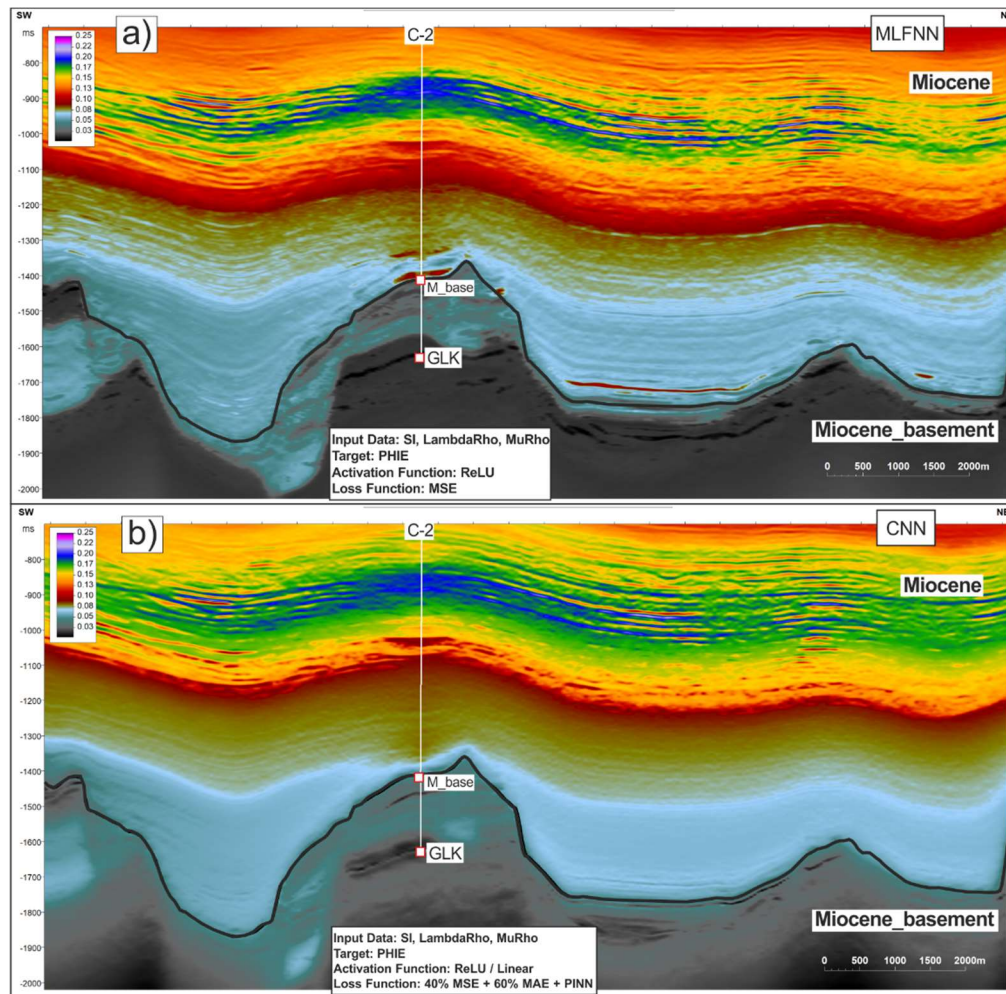


Figure 3 a) Seismic section with distribution of PHIE parameter from MLFNN; b) Seismic section with distribution of PHIE parameter from CNN

Acknowledgments

This research was funded from the funds of the Ministry of Science and Higher Education under the contract no. DWD/8/0065/2024 dated 01.10.2024, program “Implementation PhD 2024” for AGH University of Krakow and based on the statutory works—the works of the Oil and Gas Institute-National Research Institute commissioned by the Ministry of Science and Higher Education; archive number: DK-4100-0022/2025. The Authors would like to acknowledge the ORLEN PGNiG for sharing the data for research purposes and to thank them for the permission to publish the results.

References

- Aki, K. and Richards, P.G. [1980] *Quantitative Seismology. Theory and Methods*, Vol. I and II. W.H. Freeman, San Francisco.
- Gogoi, T. and Chatterjee, R. [2019] Estimation of petrophysical parameters using seismic inversion and neural network modeling in Upper Assam basin, India. *Geoscience Frontiers*, **10**, 1113-1124.
- Li, M., Yan, X.-S. and Zhang, M.-Z. [2023] A comprehensive review of seismic inversion based on neural networks. *Earth Science Informatics*, **16**, 2991-3021.
- Picha, F.J. [1996] Exploring for hydrocarbons under thrust belts-A challenging new frontier in the Carpathians and elsewhere. *AAPG Bulletin*, **80**, 1547-1564.