Improved neural network model of assessment for interpretation of miocene lithofacies in the Vukovar formation, Northern Croatia

Izboljšani nevronska-mrežni model za oceno interpretacije miocenskega litofaciesa v Vukovarski formaciji v severni Hrvaški

Varenina Andrija¹, Malvić Tomislav², Mate Režić^{3,*}

¹ Jabuka 9, 21240 Trilj

² University of Zagreb, Faculty of Mining, Geology and Petroleum Engineering, Pierottijeva 6, 10000 Zagreb, Croatia

³ Stepinčeva 16, 21000 Split

* mate.rezic92@hotmail.com

Abstract

The Ladislavci Field (oil and gas reservoirs) is located 40 km from the city of Osijek, Croatia. The oil reservoir is in structural-stratigraphic trap and Miocene rocks of the Vukovar formation (informally named as EL, F1a and F1b). The shallower gas reservoir is of Pliocene age, i.e. part of the Osijek sandstones (informally named as B). The oil reservoirs consist of limestones, breccias and conglomerates, and gas is accumulated in sandstones. Using neural networks, it was possible to interpret applicability of neural algorithm in well log analyses, and using neural model, it was possible to predict reservoir without or with small number of log data. Neural networks are trained on the data from two wells (A and B), collected from the interval starting with border of Sarmatian/Lower Pannonian (EL marker Rs7) to the well's bottom. The inputs were data from spontaneous potential (SP) and resistivity (R16 and R64) logs. They were used for neural training and validation as well as for final prediction of lithological composition in the analysed field. The multilayer perceptron (MLP) network had been selected as the most appropriate.

Key words: neural networks, Ladislavci Field, Drava Depression, Miocene, Croatia.

Povzetek

Naftno in plinsko polje Ladislavci je oddaljeno 40 km od mesta Osijeka na Hrvaškem. Naftni rezervoar je v strukturno-stratigrafski pasti v miocenskih plasteh Vukovarske formacije (delovne oznake EL, F1a in F1b). Plitvejši plinski rezervoar je pliocenske starosti, v delu osjeških peščenjakov (delovna oznaka B). Plinski rezervoar sestoji iz apnencev, breč in konglomeratov, plin je pa nakopičen v peščenjaki. Z uporabo metode nevronske mreže smo preverili uporabnost nevronskega algoritma za analizo karotažnih podatkov iz vrtin in nevronskega modela za napovedovanje rezervoarjev na osnovi majhnega števila podatkov ali celo brez njih. Učenje nevronske mreže smo izvedli s podatki iz dveh vrtin (A in B), posnetimi v intervalu od meje sarmata s spodnjim panonom (EL reper Rs7) do dna teh dveh vrtin. Uporabili smo meritve lastnega potenciala (SP) in električne upornosti (R16 in R64). S temi podatki smo izvedli nevronska učenje, validacijo in končno napovedovanje litološke sestave proučevanega polja. Kot najprimernejšo smo izbrali večslojno perceptronsko mrežo (MLP).

Ključne besede: nevronske mreže, polje Ladislavci, Dravska udorina, miocen, Hrvaška.

Introduction

Ladislavci Field (Figure 1) is located in the eastern part of the Drava Depression in the Croatian part of the Pannonian Basin System, 40 km east of Osijek, Northern Croatia. This area is predominantly a lowland with an average altitude of about 100 m. The eastern part of the Drava Depression is margined with mountains of Papuk and Krndija in the south, mostly with Drava river in the north, Mura Depression in the west and Slavonian-Srijem Depression in the east. Hydrocarbon research in this area began after geological interpretation of geophysical data collected in 1959, and the well Kučanci – 1 was constructed. The seismic sections recorded until 1973 provided better quality data on which the geological and economic basis for the project of the Ladislavci and the Kučanci structures was made. Two artificial neural networks are designed to predict wider reservoir lithofacies in the analysed field. Such lithofacies belong to the oldest Upper Miocene (Lower Pannonian) and Middle Miocene (Badenian, Sarmatian) lithofacies, i.e. lithostratigraphically had been analysed interval between e-log (EL) marker Rs7 (border between Lower

and Upper Pannonian) and well bottoms. Analysed data had been transferred into categorical variable, derived from multi-log lithological analysis. Neural model had been programmed using “JustNN” program, fed by lithofacies data and reservoir depths. The analyses had been done for two wells, here named A and B. The network with a feedback procedure and several hidden layers, i.e. multilayer perceptron (MLP) network, was used. It was proved to be most successful in predicting Miocene lithofacies in the Ladislavci Field.

Basic hydrocarbon geology settings of the Ladislavci Field

The oil reservoir of the Ladislavci Field is of Miocene age (the Vukovar Formation) and gas (the Osijek sandstones) is of Pliocene age (Figure 2). The oil reservoir is divided into three informal units (E1, F1a and F1b) [2], combined into structural-stratigraphic trap. According to Brod and Jeremenko [3] classification, it is a massive type reservoir in erosional buried hills. The reservoir rocks include limestone breccias, clastic limestones and breccias–conglom-

Figure 1. The Ladislavci Field location in the Drava Depression (Northern Croatia) [1].

Figure 2. The Ladislavci Field's stratigraphic column.

erates. The secondary porosity varies considerably even at smaller intervals. From 6 wells that drilled reservoir rocks approximately at the same structural height, only 3 discovered rocks saturated with hydrocarbons. This was indication of locally weakly permeable isolator rocks inside the Ladislavci structure. Moreover, the reservoir fault zones represented barriers during hydrocarbon migration. Frequent vertical and lateral changes in lithofacies made reservoir development very difficult. Tectonic block is the reason why oil/water contact in different wells is at different depths. This is particularly evident in well B where the oil/water

contact is 60 m deeper than that in well A. So, this contact in well B is found at -2180 m, but in the northern block, the same contact varies between -2115 and -2130 m.

Theory and application of neuronal networks

The term "neural networks" has a double meaning. Traditionally, this term referred to a biological (natural) neuron network constructed of biological neurons that are connected to the peripheral or central nervous system. Neuron

Figure 3. Human neuron model [6].

(the nerve cell) is a basic unit of the nervous system and is also the most complex unit of the human organism (Figure 3). Artificial neural networks have touch points with the human brain structure. It is common for both types of networks to transmit only two information, whether the connection is active or not, and these information are expressed by a certain electrical potential in the brain or computer. Similarity of these two networks is in the way these two states are used to make the final result as a simple processing of data. Both types of networks are based on repetitive procedures, iterations and exercises [4,5]. Artificial neural networks serve to understand biological neural networks and solve problems in the field of artificial intelligence (AI). They use the structure of the human brain to develop an appropriate data analysis strategy. Neural networks are widely used in social and technical sciences. In the following, it can be concluded that artificial neuron mimics the basic functions of biological neuron. The neural network is a set of mutually connected simple elements, units or nodes, whose functionality is based on the biological neuron. The power of analysis is to maintain the link between individual neurons, i.e. the difficulties that come from the adaptation process or by learning from the data set. The term AI is defined as any inactive system that has the ability to react in different and new situations.

Basic properties of artificial neural networks and their division

The most important properties of artificial neural networks are:

- Data processing that is distributed parallelly: Unlike conventional computing techniques, neural networks accept multiple inputs in parallel and receive processed data in a distributed manner. The data

stored in the artificial neural network are distributed to multiple computing units, which are completely in opposite to conventional data storage where each particular datum/information is stored in its own storage space. The attribute of distributed data storage gives neural networks more advantages, the most important of which being redundancy, that is, the resistance to fail, and therefore, an artificial neural network will continue to work even if some of its parts are malfunctioned.

- Learning and adaptation: The ability to learn and adapt makes neural networks capable of treating inaccurate and badly kept data in an unstructured and indefinite environment. If certain data come in network's input and the same data are not from the sample on which the network is created and based, a properly trained neural network has the ability to amplify that certain data.
- Universal approximator: The most important feature of neural networks from the point of view of modelling, identification and management of nonlinear processes is that they approximate the continuous nonlinear function to the desired accuracy.
- Multivariable systems: Neural networks are multivariable systems, and this makes them easy to apply for modelling, identification and management of multivariable processes.
- Gate implementation: More than one manufacturer has developed specialised networking systems for neural networks, which allows parallel distributed processing in real time.
- Computationally demanding neural networks: The output of each neuron is the result of sum of more products of multiplying and calculation of the nonlinear activation functions.
- The calculation speed of the neural network is determined by the number of mathematical operations of a single layer rather than the entire network: Furthermore, each layer of the network has a parallel texture, i.e. each neuron in the layer can be viewed as a local processor parallel to other neurons.

- Neural networks require a large storage space: Each individual neuron has more synaptic links, each of which is associated with a weight coefficient that must be stored in memory. By increasing the number of neurons in the network, the memory requirements increase with the square of the number of neurons.

Neurons connected to the network are organised into layers. Each network has neurons that serve to accept the input values and make the input layer of the neurons and give the network response and make the output layer of neurons. All other neurons that lie between these two layers form a hidden neuron layer (e.g. [7]). Neural networks can be single- and multi-layered. One layer network consists of one layer of neuron (output layer), while the input layer is not counted because it does not have data processing. Multilayer networks have also one or more hidden layers of neurons (e.g. [8]). The main task of the network is to learn the model of the environment in which it will work and maintain the model accurate to achieve the desired goals of the given system. Learning is a process by which free parameters of neural networks are adapted through a continuous stimulation from the environment in which the network is located (e.g. [8]). A set of rules to solve a learning problem is called a learning algorithm, which determines the way to calculate changes in synaptic weight at the time (moment, n), while the learning paradigm (learning under supervision, learning by support, learning without supervision) determines the neural network's relation to the environment (e.g. [8]). For supervised learning, training data consist of examples with known input and output values. The network generates output, accounts for a mistake (the difference between the desired and the gained values) and adjusts the synaptic weight with respect to the error. The process is repeated iteratively until the network learns to imitate the exact model. In some situations, it is not possible to provide such information or data but only data that tell whether the output value is desirable or not. This type of learning is called "reinforcement". In this kind of learning, there is no validation data set that determines what is a mistake for certain input and output

values, but it is known how much a particular learning step is good. Learning Support solves the problem of learning under supervision, that is, without a validation data set, the network cannot learn new strategies that are not covered by the examples used for learning. In unsupervised learning, output values are not known. Inputs are available in the network, and weights are not based on actual output values. Here, the artificial neural network organises itself, so the networks taught by this method are called self-organising neural networks. If the neuron layers are connected so that the signals travel in one direction from the input to the network outlet, such a network type is called the acyclic neuron network. If there is at least one feedback link, the network is called a reverse link network. By type, the neuronal linkage can be realised between two layers (between layers) and between neurons in one layer (interspersed). When a neuron receives the input from the previous layer, the value of its input is calculated by the input function, usually called a "summation" function. Activation functions are used to reduce the number of iterations. Consequently, neural networks can be divided into four main types (e.g. [7]): acyclic network, feedback network, side-by-side network and hybrid network.

Basic mathematical expressions of neural networks and working principle of artificial neural network

The output of each neuron represents the input signal modified by the corresponding function. Neuron output " j " is described in the following equations (e.g. [1]):

$$U_j = \sum \pm X_i w_{ij} \quad (1)$$

$$Y_j = F_{th} (U_j + t_j) \quad (2)$$

where j is the number of neurons, i the number of inputs, X_i the value of " i " input, w_{ij} the predetermined weight coefficient for input " i ", U_j the common value of the output of all inputs " j ", F_{th} the activation function and Y_j the output of the observed layer or the total output of the network.

When the common value U_j is computed, it is compared to the value to the threshold value

Figure 4. Sigmoidal activation function.

Figure 5. MLP network scheme.

(cut-off), i.e. the activation function F_{th} is tested. The term (1) represents a set of operations in the neuron and the other (2) examines whether this same neuron is activated.

The most common form of activation function is the sigmoidal (logistic) function. In addition to sigmoidal activation functions (Figure 4), other forms of activation functions may also be used. Sigmoidal function is defined by equation (3) (e.g. [1]) where parameter “a” determines the slope of the function:

$$f(x) = 1 / (1 + e^{-ax}) \quad (3)$$

The work of artificial neural networks can be divided into degree of learning (training), selection phase (cross validation), check phase and operational phase (degree of revocation). Two basic stages in the work of artificial neural networks are degree of training and the degree of verification. In the selection phase, the network tries to optimise the length of the training and the number of hidden neurons, after which the resulting network is stored and tested. The operational phase refers to the application of the neural network in new cases with unknown results but fixed weights. Prior to learning, it is necessary to prepare input data to which the network will be applied and define the model of artificial neural network. Data are usually divided into two sets, one is used to train the network, while the other is used for testing. It is recommended that the data set used for network training is 80% of input data and the remaining 20% of data are used for verification [9]. Learning is the process of adjusting weights in the

network that takes place in multiple repetitions (iterations). The number of repetitions usually amounts to several thousands, and if it is possible to determine the difference between the actual and desired network response, the amount of error can be returned back to the network to minimise. This process is called a “backpropagation network” (Figure 5) and is repeated so many times until the single or total error drops below the desired value. The second work stage of the network is the testing of the same being carried out so that the network presents new input values that have not participated in the network learning process and generates the corresponding output values for the input values presented. Network evaluation is done by comparing the network’s output value with the actual output value based on which error is calculated. The network no longer learns and does not expand its capabilities but only counts new values from the established amounts. The design process of artificial neural networks consists of several steps:

- defining the model (determining input and output variables);
- choosing the most suitable algorithm;
- putting neurons into layers;
- determining the type of connection between the neurons;
- determining layer functions;
- selection of training rules;
- selection of benchmarks for network assessment and
- performing a training session.

Geophysical methods used in analysis of Miocene lithofacies

Geophysical methods in selected wells include measurements of electrical resistance and spontaneous potentials (SPs; conventional electric logging) for the purpose of determining their porosity or saturation. Logging measurements were performed at the end of the 70s and 80s of the last century. This included the recording of SP values and electrical resistance with electrodes normally at a distance of 16" (R16) and 64" (R64).

First application of neural networks at Northern Croatia hydrocarbon reservoirs – the Okoli Field

This network was base for developing neural analysis in the Ladislavci Field. The network was trained on the data obtained by interpreting the e-logs (GR, R16, R64, porosity, SAND and SHALE portion) from two wells (B-1 and B-2), which drilled Miocene reservoir "c" and Pliocene "c2". From the well B-1, GR curves (curves of natural radioactivity), R16 (resistance curve – "low normal" curves) and R64 (resistance curve – "normal" curves) were used. The input curves in the B-2 well were GR, PORE (effective porosity), PORT (total porosity), PORW (porosity in the part saturated with 100% water), R16, SAND-STONE (sand portion) and SHALE (marl portion). The output curve was called a "reservoir", and it represented a "categorised" variable, defined numerically with 0 and 1. Number 0 represented marl, and number 1 represented sandstone. For learning the network, 153 data with value 0 and 142 data with value 1 from the well B-1 were used in total. For validation (V), 48 data with value 0 and 50 data with value 1 were used. Network training performances are given in Table 1. The best network was marked with a total of 31,515 iterations and a learning time of 5.40 minutes and an average learning error of 0.00173 [9]. Simultaneous training and prediction were done in the B-2.

For the learning of the network (L – learning), 225 data were used with a value of 0 and 215 data were used with a value of 1. For validation (V – validation), 71 data had value of 0 and 75 data had value of 1; therefore, 586 data from which each tenth is shown in Table 2.

Table 1. Probability of success of learning of network in well B-1 [10].

Legend: 1) Data Type, 2) "Reservoir" Variable, 3) Probability of successful prediction								
L	0	78,3	V	1	78,3	L	0	78,3
L	0	78,3	L	1	78,3	V	0	78,3
L	0	78,3	L	1	78,3	L	0	78,3
L	0	78,3	L	1	78,3	L	0	78,3
V	0	82,1	L	1	78,3	L	0	78,3
L	0	78,3	L	1	78,3	V	0	78,3
V	0	82,1	L	1	78,3	V	0	78,3
L	0	78,3	L	1	78,3	L	0	78,3
L	0	78,3	L	1	78,3	L	0	78,3
V	1	82,1	L	1	78,3	L	0	78,3
L	1	78,3	L	1	78,3	L	0	78,3

Table 2. Probability of success of learning of network in well B-1 [10].

Legend: 1) Data Type, 2) "Reservoir" Variable, 3) Probability of successful prediction								
L	0	82,1	L	1	82,1	L	0	82,1
L	0	82,1	L	1	82,1	L	0	82,1
L	0	82,1	L	1	82,1	L	0	82,1
L	0	82,1	L	1	82,1	V	0	88,1
V	0	88,1	L	1	82,1	L	0	82,1
L	0	82,1	L	1	82,1	V	0	88,1
V	0	88,1	L	1	82,1	V	0	88,1
L	0	82,1	L	1	82,1	L	0	82,1
L	0	88,1	V	1	88,1	L	0	82,1
V	0	82,1	L	1	82,1	L	0	82,1
L	1	82,1	L	1	82,1	L	0	82,1
L	1	82,1	L	1	82,1	L	0	82,1
V	1	88,1	V	1	88,1	L	0	82,1
L	1	82,1	V	1	88,1	L	0	82,1
V	1	88,1	L	1	82,1	V	0	88,1
L	1	82,1	L	1	82,1	L	0	82,1
L	1	82,1	L	1	82,1	L	0	88,1
L	1	82,1	L	1	82,1	-	-	-
L	1	82,1	V	0	88,1	-	-	-
L	1	82,1	L	0	82,1	-	-	-
L	1	82,1	V	0	88,1	-	-	-

The B-2 network was programmed to 28,599 iterations, and an average learning error of 0.002681 was obtained. The obtained values were similar to those for the B-1 well but due to the higher number of logs, the total time of training of the network was longer by about 3 times or 16.13 minutes [9]. An overview of the results obtained from the data from the well B-2 shows that the predicted and actual values have a much smaller degree of correlation. According to the facies, the prediction of 1 (or sandstone facies) is 100%. On contrary, marl (value 0) is significantly underestimated with probability of only 7.8% for correct foreseen. Numerically, of the 296 input cells described as a marl, the value 0 is correctly predicted in 23 cases and replaced by the number 1 in 273 cases. If the results obtained from the B-1 borehole are observed, a similar appearance of a marl layer replaced with sandstone can be seen. The answer lies in the type and number of used logging curves (GR, R16, R64), i.e. introducing of SP or porosity logs could improve correct distinguishing of Neogene sandstones and marls [9].

Analysis of the Ladislavci Field lithofacies using artificial neural networks

For facies analysis in the Ladislavci Field, the "JustNN" program was used, and the input data were determined by the interpretation of e-logs from wells A and B. The program can very easily load data and create a multilayer neural network. After the training, the program weighted parameters that most affected the output. The neural networks were trained at a certain depth interval. The program stopped training if the default error was reached or recorded the iteration in which the lowest selection error has been reached.

Prediction of the lithology

For the purpose of predicting the lithological composition, the reservoir (limestone breccia, clastic limestone and breccia/conglomerates) and isolator rocks (limonitised mudstone) were routinely separated from the boreholes A and B by logging diagrams. These were sep-

arated on the basis of the difference between the pass-through intervals of the permeable and nonpermeable rocks according to the position of inflection points on the SP curve. The most successful were those networks where half of the input data were used for training, while the other half were used to check the performance of the network. For the well A, network was trained on data from the range of -2153 to -2228 m and the prediction of the lithology was done from -2228 m to -2282 m. For the well B, the network was trained on data in the interval from -2122 to -2224 m, while the prediction of the lithology was made from -2224 m to -2327 m.

Analysis in the well A

The values of SP (Figure 6), resistivity (R16 and R64) and interpreted lithology were used. The analysis included 130 data, of which 66 were with a value of 1 and 64 were with a value of 0. Number 0 represents limonitised mudstone, and number 1 limestone breccia, clastic limestone and breccias-conglomerates.

The network that proved to be the most successful in training and predicting Miocene lithofacies in the well B was a reverse-feedback network (part of the MLP) with four neurons in the first hidden layer, one neuron in the sec-

Figure 6. Values of spontaneous potential in the well A.

Figure 7. Learning of the neural network in the well A (y-axis represents error values and x-axis represents number of iterations. The red line represents the largest, the green line represents the average and the blue line represents the lowest error of the training.).

Figure 8. Training MLP network on data from the well A.

Figure 9. MLP network prediction in well A.

ond hidden layer and two in the third hidden layer (Figure 7), including 8199 iterations and an average error of 0.024865 (Figure 8). The network set is divided so that one half is used for training and the other half is used for validation. The SP log was the most important network variable.

The network was trained at a range of -2153 to -2228 m. For the training, 65 data were used. According to the error, it can be concluded that the network is rather poorly trained and has not successfully determined the layer boundaries. It could be explained by a small number of input data. From Figure 9, it is apparent that the network replaced non-permeable layers with permeable layers in the range of -2183 m to -2187 m.

To determine the network performance in well A, 65 data were used. From Figure 10, it is apparent that the results are bad and that the network has not successfully determined the layer boundaries and lithological composition.

Analysis in the well B

Data used for training of artificial neural network were the values of SP (Figure 11), resistivity (R16 and R64) and the lithological composition. The input data were taken from the depth of the EK marker Rs7 (-2122 m) to the bottom of the well (-2327 m), each 1 m. Total of 205 data were analysed, of which 77 were with a value of 1 and 128 with 0. The number 0 represented limonitised claystone, and the number 1 represented limestone breccia, clastic limestone and breccia-conglomerates.

The most successful network in training and predicting Miocene lithofacies in the well B was a reverse-feedback network (type of MLP) with four neurons in the first hidden layer, five in the second hidden layer and two in the third hidden layer (Figure 12) and was marked with a total of 15,658 iterations and an average error of 0.016835 (Figure 13). The network training data set was divided so that one half of the set was used for training and the other half was used for determining network performance.

The network is trained at an interval of -2122 m to -2224 m with 103 input data. Although the amount of error is smaller than that in the previous analysis, it can be seen that the network has not successfully predicted the boundary

Figure 10. Values of spontaneous potential for well A.

Figure 11. Architecture of artificial neural network used for the prediction of Miocene lithofacies in the well B.

of the layers. It is explained by the size of the input data set and the frequent vertical and lateral changes in the reservoir rocks of the La-dislavci Field. Network learning could be probably largely improved with GR log and calliper.

Figure 12. Learning of the neural network in the well A (y-axis represents error values and x-axis represents number of iterations. The red line represents the largest, green line represents the average and the blue line represents the lowest error of the training).

Conclusion

Two artificial nerve networks were constructed with feedback procedure and several hidden layers. These MLP networks had been used for prediction of the Miocene lithofacies in the Ladislavci Field. The data sets were divided so that one half is used for training and the other half for is used for validation of the network. The network that proved to be the most successful in the training and prediction of Miocene lithofacies was a network with feedback information (MLP). In the well A, it had four neurons in the first hidden layer, one in the second hidden layer and two in the third hidden layer. In the well B, the most successful was the network with four neurons in the first hidden layer, five in the second hidden layer and two in the third hidden layer. The main results and recommendations are as follows:

- The SP log is the most important parameter through which the neural network was used for prediction of lithology and has about 3 times greater relative importance in relation to the R16 and R64 logs during network training.
- Networks had not successfully determined layer boundaries, which can be ex-

plained by a small number of input data and a complex reservoir lithology.

- The frequent vertical and lateral changes in the reservoir rocks of the Ladislavci Field made training and prediction difficult.
- In the well A, the network replaced the impermeable layers in the range of -2183 to -2187 m.
- In the well B, the network replaced impermeable sections in the range of -2197 to -2209 m.
- The probability of successful prediction of lithofacies in the well A was 61.5% and in the well B was 63.1%.
- In the well A, an actual and predicted position of limonitised claystone was matched with 46.6% and limestone breccia was matched with 67.3%.
- In the well B, limonitised claystone was matched with 63.1% and limestone breccia was matched with 58.18%.
- To obtain better results for lithological prediction, it was recommended to use GR log (natural radioactivity), calliper, compensated neutron (CN) density and density (DEN) log.

Although the results do not indicate full potential of neural networks in petroleum exploration, they are a useful tool. The problem noted here is a small thickness of individual reservoir units and consequently a small number of input data, so the error is relatively large. Another problem is that reservoirs are heterogeneous. Because of this, logs are not developed as theoretical ones. The analysis had shown that this type of network can be used in the Ladislavci Field as an auxiliary tool at those intervals of deposits that are not logged in details or not logged at all.

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