Clastic facies prediction using neural network (case study from Okoli field)

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PRELIMINARY COMMUNICATION

The Okoli field, located in the Sava depression, is selected as the example for clastic facies prediction using neural network. The significant oil and gas reserves are proved in Lower Pontian sandstone. Reservoirs of this age are the regional proved play, where also new economic hydrocarbon discoveries are expected.
This paper presents the detailed methodology using neural networks in reservoir facies prediction. The basics of neural networks are given in the introduction, while the advanced learning algorithm RProp used as a basis for the presented analysis is also described. The network is trained using log data (curves GR, R_{16}", R_{64}", PORE/T/W, SAND & SHALE) from two wells (code names B-1 & B-2). Both of them drilled production "c" series and c_2 reservoir (as analytical target) of Lower Pontian age. The real position of reservoir sandstone (c_2) in relation to top and bottom marls is registered, and the neural network was trained based on selected part of input data and registered lithology. Based on the rest of the input data, and without calibration on the real lithology, the positions of the facies (sand/marl sequences) were predicted.
The results indicate an over-trained network in the case of sandstone sequences prediction. The marl sequences at the top and base are mostly replaced by sandstone. On the other hand, such analysis pointed out that in further facies modelling in the Sava depression, performed by neural tools, the set of log curves needs to be expanded with additional curves characterizing lithology and saturation (SP, CN, DEN). Also, quality and useful prediction by RPORP algorithm could be reached with more than 90 % probability of true prediction (in presented analysis this value reached 82.1 %).

Key words: neural networks, RProp algorithm, facies, Lower Pontian, Okoli field, Croatia

1. INTRODUCTION

The Okoli field was selected as the study area for facies analysis. This field is located in the western part of the Sava depression (Fig. 1). The position of sandstone and marlstone sequences in "c" series (c_2 reservoir as well as top and bottom marlstone) in the wells B-1 and B-2 at the Okoli field was predicted using neural network. The c_2 reservoir was selected regarding relatively high homogeneity of Lower Pontian sandstone as well as typical clastic sequence deposited in Upper Pannonian and Lower Pontian periods in the entire Croatian part of the Pannonian Basin. Applicability of neural network in Upper Miocene clastic lithology prediction was checked and described, using log curves from the Sava depression. The analysis was performed by cVision program, product of the Neuro Genetic Solution (NGS) company.

2. NEURAL NETWORKS - BASIC CONCEPT

Generally, neural networks are modern tools with numerous purposes1. In the early days of artificial intelligence ROSENBLATT, employed at the Cornell Aeronautical Laboratory, was developed in the 1957 machine called perceptron, based on memorizing the pattern of the human mind[2,3]. Such a machine could "learn" and represent the prototype of a neural network. The Perceptron scheme included connections like those in an associative memory.

The basic structure of the network is based on an artificial neuron model (Figure 2). Such a neuron is assembled from several inputs and a single output. Each input is associated with related weight added to the input

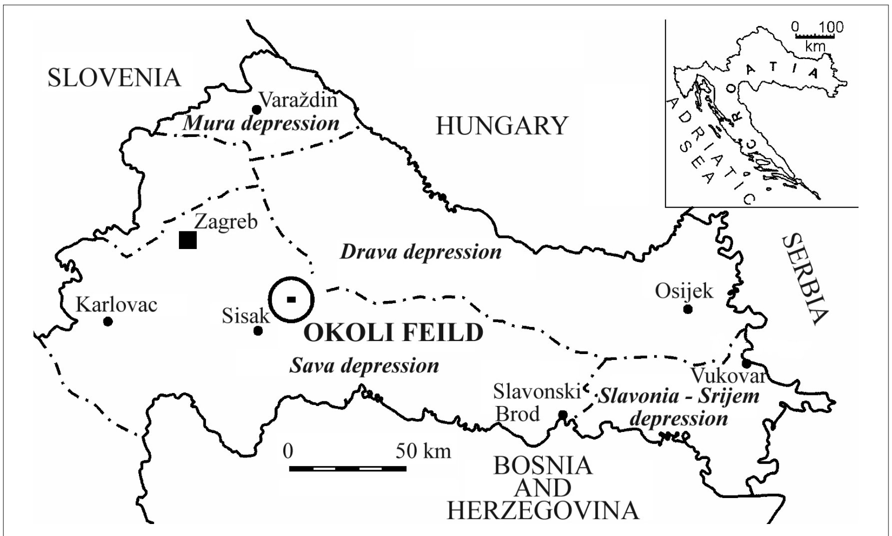

Fig. 1. Location of Okoli field within the Croatian part of the Pannonian Basin
Sl. 1. Položaj polja Okoli unutar hrvatskog dijela Panonskog bazena

value. Depending on the result, the neuron could stay inactive or be activated. The values and conditions for activation are determined by the activation function.

Specific number of neurons defines a network is described through *layers* (Figure 3). The set of selected neurons make an *input* layer. Such inputs are modified through *hidden layers* and the result is given in the *output* layer. Hidden layers are not connected with information outside the network, like inputs or the output channels.

In general, the input layer collects and distributes data loaded into the network, while the hidden layer(s) process such data, using the activation function. Expression (1) represents a set of operations performed on the neuron, and equation (2) detects activation of the neuron.

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

Where:

- j Number of neurons
- i Number of inputs
- X_i Value of input "i"
- w_{ij} Previously determined weight coefficient for input *"i"*
- U_j - Value of output in neuron *"j"*

$$Y_j = F(U_j + t_j) \quad (2)$$

Where:

- F Activation function
- tj Target value for neuron *"j"*
- Yj Layer output (or total output if it is the last layer)

The value of output *(U_j)* is compared with conditions necessary for hypothesis acceptance *(t_j)*. The activation function *(F)* is eventually started based on this value.

Expression (1) implies previously determined weighting coefficients, value of hypothesis acceptance, number of layers and number of neurons in each layer. This makes it possible to obtain a result from the neural network. The values of the weighting coefficients and hypothesis acceptance are changed and modified in the period of network training (or learning).

Recognition of samples that could only be separated using linearity represents the limits of a network based only on perceptrons. This limitation is overcome by introducing the back *error propagation* paradigm (abbr. backprop). This algorithm extends the perceptron effect, using a large number of hidden layers. This is why term the multiple layer perceptron (abbr. MPL) is used.

Backpropagation algorithm means that network training includes determination of

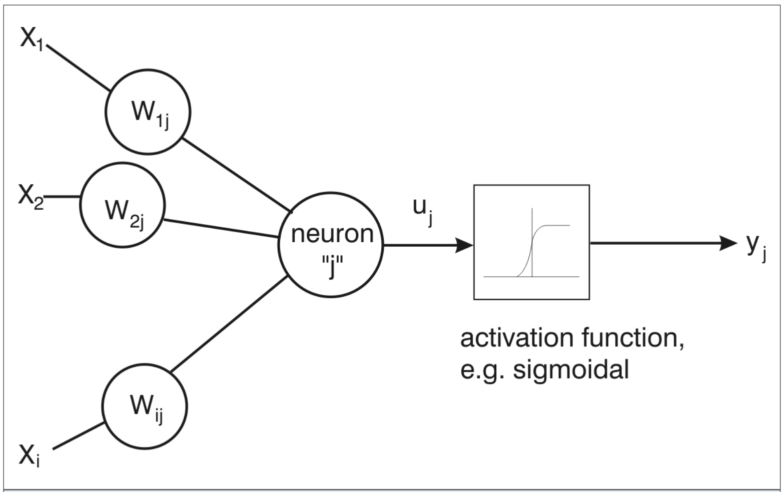

Fig. 2. The artificial neuron model
Sl. 2. Model umjetnog neurona

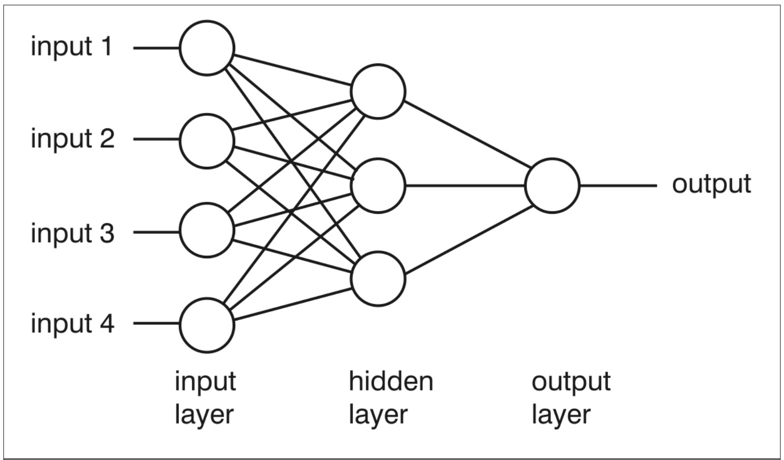

Fig. 3. Schematic organization of neural network through layers
Sl. 3. Shema organizacije neuronske mreže preko slojeva

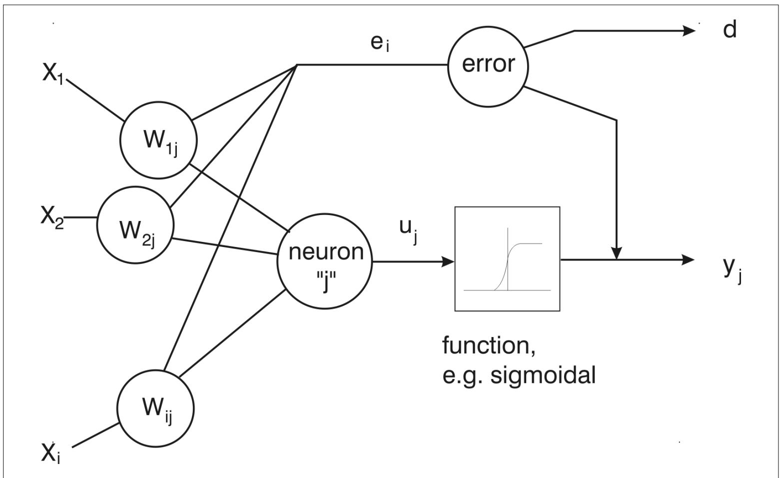

Fig. 4. Adoption of weighting coefficient and error decreasing
Sl. 4. Prilagođivanje težinskih koeficijenata i smanjivanje pogreške

the difference between true and wanted network response, i.e. means calculation of *error* that is backed in the network for obtaining optimal training (Figure 4). Such an error is determined for each neuron and used for adopting the existing weighting coefficient and activation value.

Such a corrective procedure is called the *backpropagation network* that describes the process of network learning and validation. It is repeated so many times until the particular or total error is decreased below the limit. Thereupon, the training is over and the network could be applied for processing new inputs. *The backprop* algorithm first processes inputs, checks output error, and finally goes back to the same inputs. It is the most popular paradigm that is applied for neural network. Backprop of information in the network always starts from the output to the inputs. The weighting coefficients and error calculation are shown in equations (3) and (4).

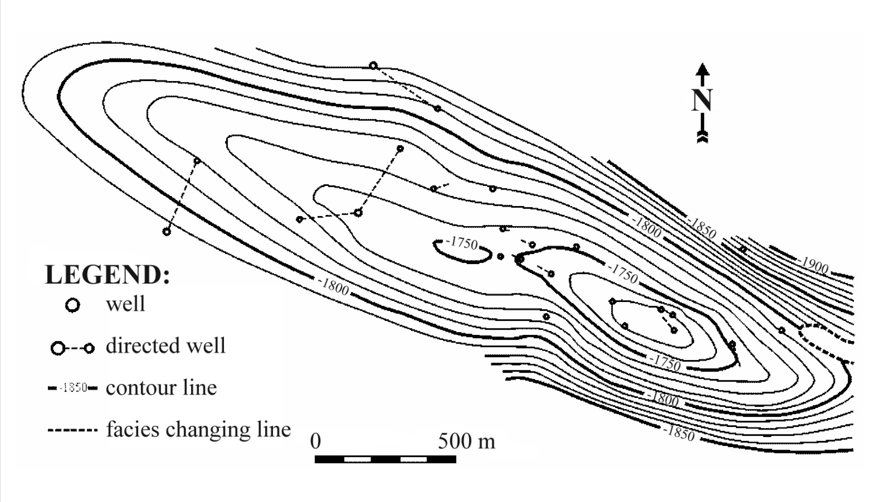

Fig. 5. Structural map of a_1 reservoir top [9]
Sl. 5. Oblik strukture po krovini ležišta a_1 [9]

$$w_{ij} = w_{ij}^{*} + LR \times e_j \times X_i \tag{3}$$

Where:

- i Number of inputs in neuron *"j"* in output layer
- j Number of neuron
- w_{ij} Weighting coefficients
- w_{ij}^{*} Correction of weighting coefficients resulted from training
- LR Learning rate
- e_j Error rate
- X_i Value of input *"i"*

$$e_j = Y_j \times \left(1 - Y_j\right) \times \left(d_j - Y_j\right) \tag{4}$$

Where:

- Y_j True output
- d_j Wanted output

The learning rate influences the previously determined weighting coefficients and calculation of new ones. It usually fits as a lower value and could be increased if training is too slow.

Backprop is used in multilayer networks, but often could be characterized with long lasting training. This is why using the backprop is limited for calculation without inquiries for fast outputs. Such shortage in the learning rate resulted from *the gradient descent* method used in the backprop algorithm.

Some limitations occure relatively often in standard neural networks applications in geophysics4. Such a standard network only allows sending information to previous layers, i.e. back. It can significantly decrease the learning rate, and sometimes adjustment of weighting coefficients can completely paralyze the network.

Today, there are several other algorithms that can increase the training speed. One of them is *the Resilient Propagation Algorithm*[5] (abbr. RProp). The main difference, after the standard backprop algorithm, is expressed through using only partial derivations in the process of weighting coefficient adjustment[6]. RProp uses so-called training through epochs, where weighting coefficients are adjusted after all the patterns or connections for input data are set. Finally, RProp is 4-5 times faster than the standard backprop algorithm.

3. BASIC GEOLOGICAL RELATIONS AND PREVIOUS FACIES MODELLING PERFORMED AT THE OKOLI FIELD

The Okoli field encompasses several sandstone series, and each of them is divided in reservoirs. The field structure is brachianticline with strike NW-SE (Figure 5), and faulted in deeper parts. Reservoirs have Upper Pontian ("b" and "c" series) and Pliocene ages ("p", "A", "B" and "a" series). Totally 11 reservoirs were drilled through series "c" (c_1-c_{11}). The series "a" (reservoirs a_1, a_2, a_3) is mostly used for squeezing and accumulating of gas, while series "b" and "c" represent gas-production intervals. Sandstone porosity varies between 14 and 37 %, and permeability 1.3 and 24.8 x 10^{-3} μm² (see 7,8). Reservoir thickness ranges from 1 to 20 meters.

Log curves were taken from the company database. Particular intervals of c_2 reservoir are outlined. The entire "c" series was deposited over the major part of the field, and particular reservoirs are concordant (continuous), characterized by locally correlative marlstones in the top and bottom of sandstones.

In the B-1 well, marlstone in the top and bottom of c_2 reservoir is bordered by c_1 and c_3 reservoirs (normal concordant sequence shown in Table 1).

In the B-2 well, equivalent borders are represented by c_1 and c_4 reservoirs (c_3 reservoir is not sedimented in sand facies, shown in Table 1). The B-1 well is located close to structure top, and B-2 well on the NW margin.

Table 1. Depth of c_1 - c_4 reservoirs in analyzed wells

Reservoir	B-1 well Absolute depth (in meters)	B-2 well Absolute depth (in meters)
c_1	2 088.5 – 2 098.5	2 123.0 – 2 125.5
Marlstone	2 098.5 – 2 108.5	2 125.5 – 2 135.0
c_2	2 108.5 – 2 132.5	2 135.0 – 2 164.0
Marlstone	2 132.5 – 2 147.5	2 164.0 – missing
c_3	2 147.5 – 2 152.0	missing – missing
Marlstone	2 152.0 – 2 159.5	missing – 2 184.0
c_4	2 159.5 – 2 177.5	2 184.0 – 2 192.0

The structural map of the c_2 reservoir top is shown in Figure 6.

The following log curves were applied in B-1 well: GR (gamma ray), $R_{16"}$ and $R_{64"}$ (resistivity logs).

In B-2 wells the selected log curves were: GR (gamma ray), PORE (effective porosity), PORT (total/true porosity), PORW (porosity in rock part 100 % saturated with water), $R_{16"}$ (resistivity), SANDSTONE (sand portion curve) and SHALE (marl portion curve).

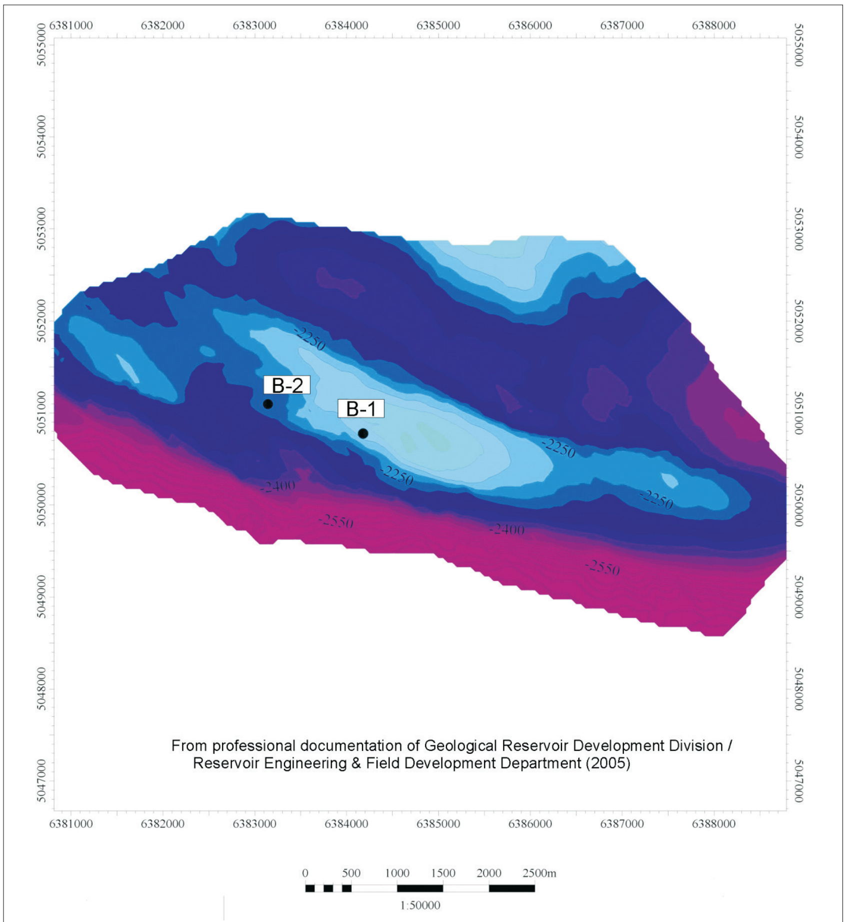

Fig. 6. Structural map of the c_2 reservoir top with selected well positions
Sl. 6. Strukturna karta po krovini ležišta c_2 s naznačenim položajem dviju analiziranih bušotina

The new calculated curve, in both cases, was called LEŽIŠTE (RESERVOIR). This curve represents artificial "categorized" variable, defined with numerical values 0 and 1. Value 0 shows marlstone, and value 1 sandstone. Such categorized values, listed according to depth, describe reservoir facies as well as top and bottom marlstones. The analytical target was prediction of the true position of values 0 and 1 (i.e. sandstone and marlstone sequences) using CVision software, i.e. reconstruction value of the variable LEŽIŠTE as accurately as possible.

The Okoli field was previously analyzed through numerous geological researches. Facies analysis indicated homogeneity that could be described mathematically. Geostatistical facies researching[10] included calculation of experimental semivariograms for porosity and permeability, from a_1 reservoir data. The variogram interpretation was based on recognizing semivariogram trends in different clastic reservoirs[11]. Reservoirs of "a" series are divided in zones where petrophysical parameters vary in different intervals. Several such zones could be connected in one larger entirety, enabling observation of the cyclic trend in porosity increasing in deeper intervals. Variogram porosity range in a1 reservoir is 3.2 - 5.3 meters, i.e. spatial dependence was proven for such a distance, meaning that porosity values could be extrapolated for the mentioned ranges outside the cores in "a" series. Variogram permeability range is 2.2 meters.

The results indicated that petrophysical values, as well as the Okoli field facies, could be described and predicted using geomathematical tools.

4. cVISION PROGRAM

Facies analysis of the Okoli field was performed by the cVision program (trial license), programmed by ***Neuro Genetic***

Solution (NGS). This company develops programs and analysis data for exploration and development purposes of oil and gas reservoirs. The mentioned program is a neural network product, used for establishing connections in analytical data[12]. It is prepared for users without significant experience in programming and using neural technology. Most input data for the network can be adjusted automatically or by introducing relatively simple minor changes using templates. The user, interested in the quality use of the program, needs to gain basic knowledge about neural networks and understand the basic terms, especially in adjusting default values.

Upon installation, cVision is loaded as an MsExcel™ Addin, with corresponding drivers and kernel. The program uses numerical and textual inputs and outputs, and data may be loaded from one or more Excel sheets. Each sheet includes one or more channels (listed in columns).

A large part of the computer code is exclusively developed for cVision. It is important to mention the part called *Local Adaptive Learning Rules* that enable the user elementary knowledge of the term *Rate Learning*. In addition, each synaptic connection (Figures 5 and 6) in a network has its own learning rate, optimized through training. The process of network size calculation is also automated, which prevents suffocation during modeling, i.e. over-dimensioning due to memorizing irrelevant data like "noise" (i.e. null-values). Inside the layer, all hidden neurons are connected toward the output, using all possible combinations. Such architecture is called the *Completely Connected Perceptrons* (abbr. CCP).

The Okoli field data preparation included defining input curves and Excel tables, as well as selection of data in groups for *learning (L)*, *validation (V)* and *testing (T)* of the network.

4.1. Neural network type

Here selected is the *Completely Connected Perceptron* network type. The best network was chosen regarding value of error domain. The error was calculated according to validation error. *The number of experts in a cluster* defines the number of network modules with different initial conditions. Here selected is the value of 10 experts. The basic value for initializing the first expert in a cluster is called *random seed value*. Initial value is 0.01. The next expert was initiated with the previous value increased by 1. The network growth was programmed architecturally, meaning that the network was built with an increasing number of hidden layers to maximal value.

4.2. Neural network training

Training options define the initial learning rate and rules. In this analysis, the local adaptive rule called *Improved Resilient Propagation Plus* (abbr. iRProp+) was selected. The initial learning rate was set at 0.01, and this value was self-adjusted during training.

Also, inside the network are defined the criteria by which to stop training when reached. The first parameter is the error domain; when the domain value decreases below the limit, training is stopped. Such a criterion is used in this analysis. The second parameter is the number of maximum epochs in training, and when this number is reached, training is finished, although the error is not below the limit.

4.3. Neural network outputs

The results of cVision are represented through several tables and graphs, generated in Excel. These results are divided in groups for three network types, which resulted from the analysis. Each analysis includes a number of iterations or, simplified, a number of steps in the process of adjusting weighting coefficients through training.

The Face machine includes results about the best network obtained through the entire training, and these outputs are used in this paper as a measure of the networkžs successful work. *The Best machine* encompasses data of momentarily the best iteration. *The Trip machine* includes a series of the most successful iterations obtained in the entire analysis (face and best machines are part of the trip machine series).

Tables **@Monitor (D)** and **@Monitor (S)** (Tables 2 and 5) comprise several outputs:

- Columns 1-2 include information about the network type,
- Column 3 shows interval time when a particular network occurred,
- Column 4 shows iteration,
- Column 5 epochs,
- Columns 6-20 include data about different errors, and columns 6-9 the errors described as *F:LErr, F:LErr:lo, F:LErr:av, F:LErr:hi.*

The symbol **F** represents *the Face Machine*, **L** – *learning data*, **Err** – *error*, **Err:lo** – *the lowest error*, **Err:av** – *the average error*, and **Err:hi** – *the highest error*. The same information applies to validation and testing data. All listed error values also apply for the best and trip machines.

Tables **@Monitor (G)** includes a clear graphical presentation of the training process (Figures 7, 8, 9 and 10) and errors, i.e. it is a summary of data collected from table *@Monitor (S)*. The first diagram (Figures 7 and 9) shows the relation between wanted and true output, and the best configuration is symbolized with a "diamond". The second diagram (Figures 8 and 10) describes the relation between errors and the number of iterations.

Table **@OD.data** gives the purposes of data (for *validation* or *learning*), and the amount of error difference (or probability of successful prediction) between predicted and true values (Tables 3 and 6). Table **@IP.data** gives a list of true and predicted values in columns for the chosen input dataset as well as the probability that such a dataset (using a trained network) can give a true prediction (Table 4).

5. RESULTS OF FACIES ANALYSIS OF C_2 RESERVOIR

These results are given separately for B-1 and B-2 wells. The summary is presented in the conclusion.

5.1. Network testing in B-1 well

The following log curves were used from B-1 well: GR, $R_{16"}$ and $R_{64"}$. Graphical results of the network training are shown in Figures 7 and 8. The learning process (L) is performed with 153 data with value 0, and 142 data with value 1. Validation (V) is done by using 48 data with value 0, and 50 data with value 1.

Information on the total number of iterations (31 515), training time (5.40 minutes) and average learning error (0.001 73) for the Face machine are given in Table 2.

The amount of average error (0.001 7) is subsequently given as a percentage of the predicted values of variable LEŽIŠTE in the period of learning (L) and validation (V). Such a table is almost always very large, because it contains the entire input dataset. For B-1 well, there were

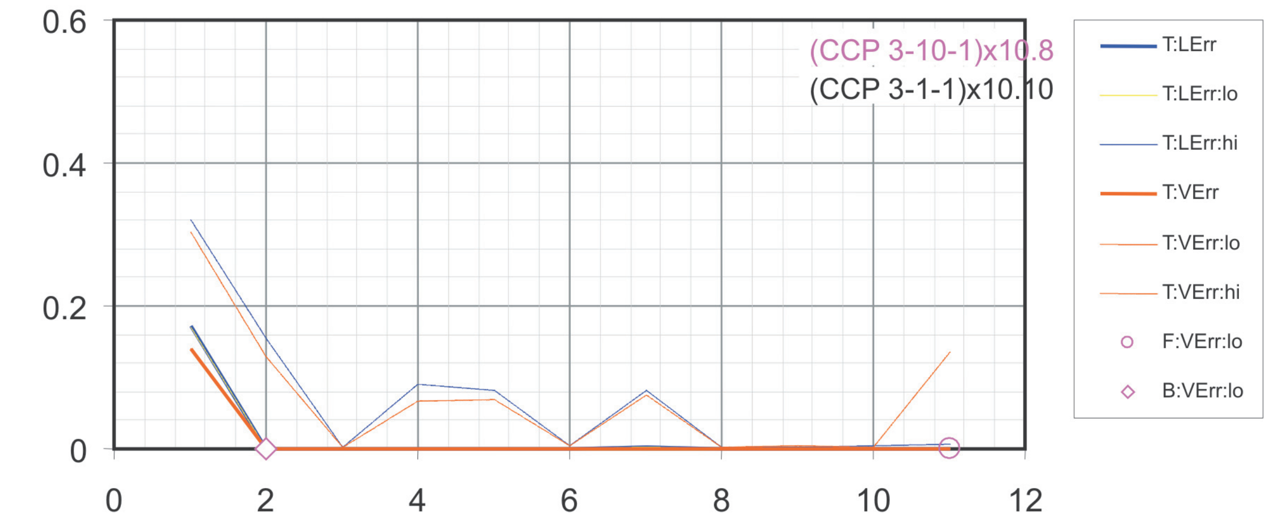

Fig. 7. Relations of errors in periods of training (T), learning (L) and validation (V) and position of Face and Best configurations (the symbols F, B in legend) for B-1 well
Sl. 7. Odnos pogrešaka tijekom treniranja (T), učenja (L) i provjere (V) te položaj Face i Best konfiguracija (oznake F, B u legendi) za bušotinu B-1

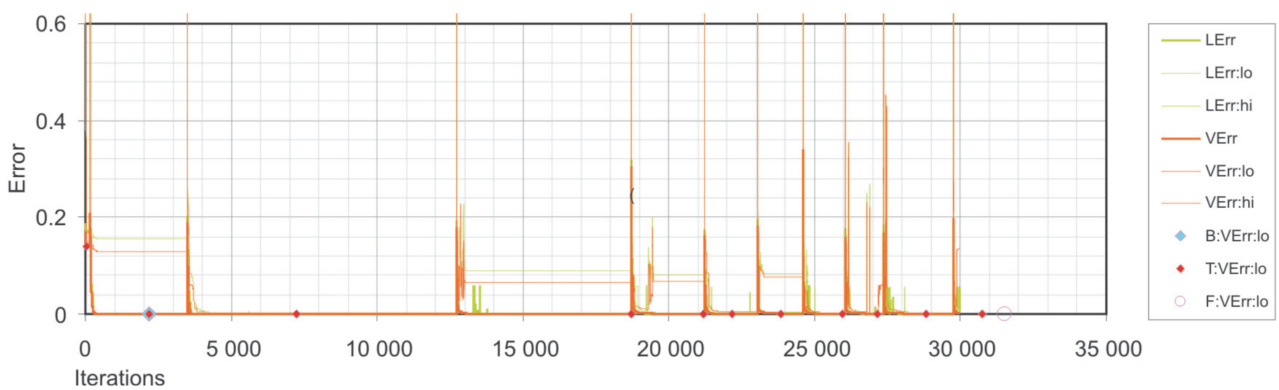

Fig. 8. Error variation observed through iterations and positions of Face and Best machines for B-1 well
Sl. 8. Varijacija pogreške kroz iteracije te položaj Face i Best konfiguracija za buš. B-1

Table 2. Parameters of the Face machine for B-1 well

Face:AID	F:SID	F:CPU	F:It	F:Ep	F:Ge	F:LErr	F:LErr:lo	F:LErr:hi	F:LErr:av
(CCP 3-10-1)x10.8	(EF).8	0:05:40	31 515	1 764	11	0.001 03	0.000 931 98	0.005 863 2	0.001 735 57

Table 3. Probability of successful network learning and validation for B-1 well

Type of input	Categorized variable LEŽIŠTE	Probability of successful Prediction %	Type of input	Categorized variable LEŽIŠTE	Probability of successful Prediction %	Type of input	Categorized variable LEŽIŠTE	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	82.1
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	82.1
V	0	82.1	L	1	78.3	V	0	82.1
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
L	1	78.3	L	1	78.3	V	0	82.1
V	1	82.1	L	0	78.3	N/A	N/A	N/A
L	1	82.1	L	0	82.1	N/A	N/A	N/A

Table 4. Comparison of results of network training and calculated values of variable LEŽIŠTE for B-1 well

Predicted value (facies)	True value (facies) var. LEŽIŠTE	Probability of successful prediction %	Predicted value (facies)	True value (facies) var. LEŽIŠTE	Probability of successful prediction %	Predicted value (facies)	True value (facies) var. LEŽIŠTE	Probability of successful prediction %
1	0	88.1	1	1	88.1	1	0	88.1
1	0	88.1	1	1	88.1	1	0	88.1
1	0	88.1	1	1	88.1	1	0	88.1
1	0	88.1	1	1	88.1	1	0	88.1
1	0	88.1	1	1	88.1	1	0	88.1
1	0	88.1	1	1	88.1	1	0	88.1
1	0	88.1	1	1	88.1	1	0	88.1
1	0	88.1	1	1	88.1	1	0	88.1
1	0	88.1	1	1	88.1	1	0	88.1
1	0	88.1	1	1	88.1	1	0	88.1
1	1	88.1	1	1	88.1	0	0	88.1
1	1	88.1	1	1	88.1	0	0	88.1
1	1	88.1	1	1	88.1	1	0	88.1
1	1	88.1	1	1	88.1	1	0	88.1
1	1	88.1	1	1	88.1	1	0	88.1
1	1	88.1	1	1	88.1	1	0	88.1
1	1	88.1	1	1	88.1	1	0	88.1
1	1	88.1	1	1	88.1	N/A	N/A	N/A
1	1	88.1	1	0	88.1	N/A	N/A	N/A
1	1	88.1	1	0	88.1	N/A	N/A	N/A
1	1	88.1	1	0	88.1	N/A	N/A	N/A

393 such data, which was why each tenth item was driven out and shown in Table 3 (but the structure of the input set was kept). It is also possible to read the percentage of the network "self"-prediction for successful learning. This value was not lower than 78.3 % (L - learning, V -validation).

The neural network in B-1 well was trained and validated for 393 data (Table 3). The optimal algorithm (the Face machine) was used for training data from log curves GR, R16", R64", in order to predict a new categorized variable (equivalent of variable LEŽIŠTE) for the entire logged interval. In the best case, such new values would need to correspond to the values of variable LEŽIŠTE. The results of the new variable (as a result of the network training) are given in Table 4.

Predicted and true results are not identical. The probability of successful prediction of 0 or 1 in the network was estimated with probability greater than 83.8 % for the entire reservoir. In addition, Table 4 shows that predicted and true values are much less similar.

In the case of value 1 prediction (sandstone facies) the similarity is 100 %. However, top and bottom marlstone (value 0) are predicted very different from the true lithology. Only in 7.8 % cases, the true marlstone value (0) was predicted. Value 0 is correctly predicted in 23 from 296 input cells, and replaced by 1 in 273 cells.

The question is why a large number of marl intervals is replaced by sands. The kind and number of logs indicates the answer. Three logs were used, one of them represents natural radioactivity and others resistivity. It could be assumed that analysis (also) based on spontaneous potential curve and porosity logs (sonic logs, density logs, neutron logs) could lead to significantly easier distinguishing between marls and sandstones by neural algorithm.

5.2. Network testing in B-2 well

The following log curves from B-2 well were used: GR, PORE, PORT, PORW, $R_{16"}$, $R_{64"}$, SANDSTONE and SHALE. Graphical results of the network training are shown in Figures 9 and 10. The learning process (L) is performed with 225 data of value 0, and 215 data of value 1. Validation (V) used 71 data of value 0, and 75 data of value 1.

The number of iterations (28 599) and average error (0.002 681) are similar to identical variables obtained in B-1 well (Figures 7 and 8). Due to more log curves, the

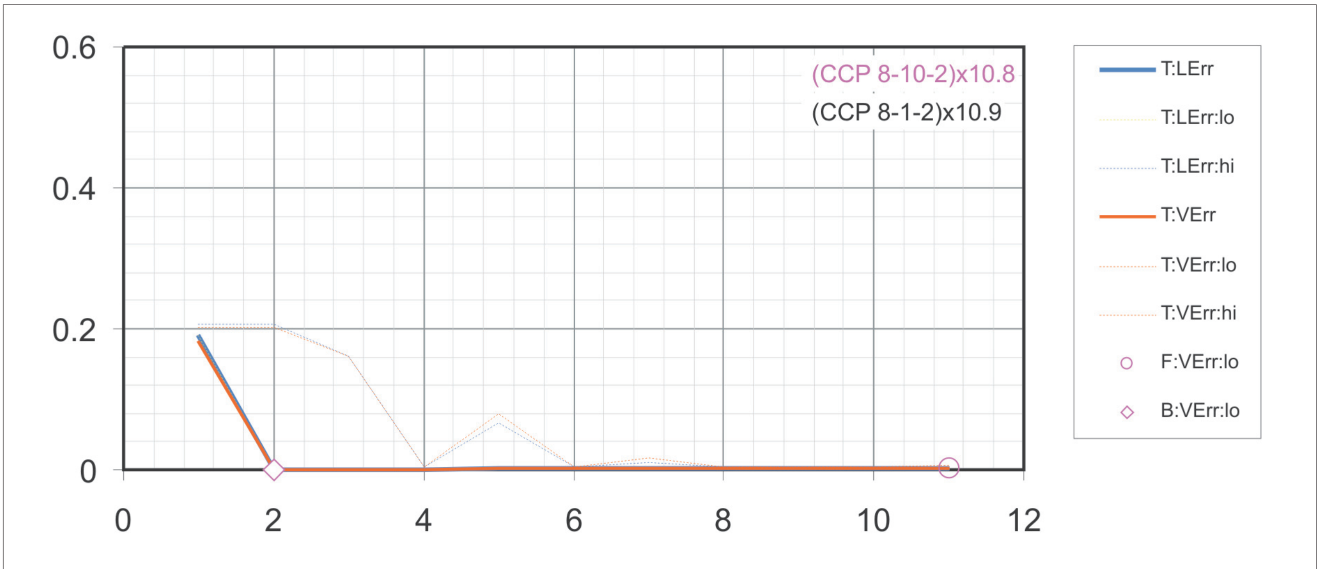

Fig. 9. Relations of errors in periods of training (T), learning (L) and validation (V) and position of Face and Best configurations (the symbols F, B in legend) for B-2 well

Sl. 9. Odnos pogrešaka tijekom treniranja (T), učenja (L) i provjere te položaj Face i Best konfiguracija (oznake F, B u legendi) za bušotinu B-2

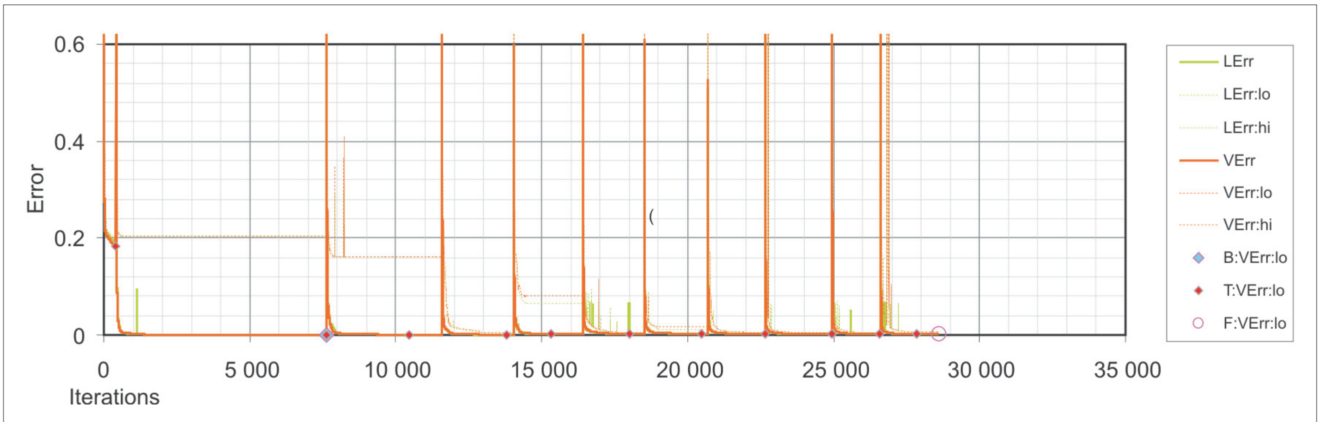

Fig. 10. Error variation observed through iterations and positions of Face and Best machines for B-2 well

Sl. 10. Varijacija pogreške kroz iteracije te položaj Face i Best konfiguracija za buš. B-2

Table 5. Parameters of the Face machine for B-2 well

Face:AID	F:SID	F:CPU	F:It	F:Ep	F:LErr	F:LErr:lo	F:LErr:hi	F:LErr:av
(CCP 8-10-2)x10.8	(EF).8	0:16:13	28 599	1 992	0.001 7	0.001 698 8	0.005 052 4	0.002 681 39

Table 6. Probability of successful network learning and validation for B-2 well

Type of input	Categorized variable LEŽIŠTE	Probability of successful Prediction %	Type of input	Categorized variable LEŽIŠTE	Probability of successful Prediction %	Type of input	Categorized variable LEŽIŠTE	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	82.1	V	1	88.1	L	0	82.1
V	0	88.1	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	82.1
L	1	82.1	L	1	82.1	N/A	N/A	N/A
L	1	82.1	V	0	88.1	N/A	N/A	N/A
L	1	82.1	L	0	82.1	N/A	N/A	N/A
L	1	82.1	V	0	88.1	N/A	N/A	N/A

total network analysis time is about 3 times longer (16.13 minutes). The information about the Face machine for B-2 well is given in Table 5.

Probabilities for successful network learning and validation in B-2 well are given in Table 6, showing each tenth item from a total of 586 inputs.

As opposed to the corresponding probability obtained for B-1 well (78.3 % in Table 3), due to more log curves applied in B-2 well the probability of successful prediction calculated in cVision is equal or greater than 82.1 %.

Prediction analysis of variable LEŽIŠTE value in B-2 well, using the Face machine (procedure shown for B-1 well in Table 4) unfortunately could not be done, because trial period had expired.

6. CONCLUSION

This was one of the first attempts in using neural tools in reservoir data analysis in Croatia. Therefore, the presented results need to be considered as guidelines for similar analyses, selection of measurement data and general purpose of such analyses. The described case study is relevant for clastic facies prediction in Lower Pannonian sediments of the Sava depression. The obtained results can be a basis for further neural facies analyses in the Croatian part of the Pannonian Basin. The main achievements are given in the following 7 items:

1. Excellent correlation between predicted and true position of sandstone lithology (reservoir) was obtained;

2. Contrarily, positions of predicted and true marlstone positions (in top and bottom) mostly do not correspond;

3. The facies probabilities calculated in the program (i.e. lithology prediction) are extremely high. In B-1 well (based on 3 log curves) it is minimal 78.3 %, and in B-2 well (based on 7 log curves) minimal 82.1 %;

4. *The Face machine* is calculated relatively in the early period of network training. In B-1 well this machine is observed in the 2186th iteration, and in B-2 well in the 7626th iteration. Such results point out that similar facies analyses in the Sava depression do not need such a large iteration set (about 30 000). The larger positive impact could be obtained by increasing the number of relevant input log curves;

5. Based on the mentioned results, the network could be characterized as over-trained, and including enough criteria for recognizing marlstone sequences;

6. Eventually, in the following neuron analyses in clastic deposits of Pannonian and Pontian ages, the input dataset would need to be extended on other log curves. Such curves would need to well characterize lithology, porosity and saturation, like SP (spontaneous potential), CN (compensated neutron), DEN (density) and some other.

7. It is assumed that the presented neural technique could be useful in log curves analysis, if the *Face machine* would be configured with 90 % probability for true prediction.

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UDK : 550.8 : 553.98 : 553.28 (497.5)

550.8	geološka istraživanja
553.98	ležišta nafte i plina, rezerve
553.28	vrste ležišta
(497.5)	R Hrvatska, polje Okoli