SELECTION OF THE MOST SUCCESFUL NEURAL NETWORK ALGORITHM FOR THE PORPUSE OF SUBSURFACE VELOCITY MODELING, EXAMPLE FROM SAVA DEPRESSION, CROATIA

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An accurate time to depth conversion between seismic and well data (velocity modeling) is often a challenge in those hydrocarbon fields which were developed in the second part of the 20th century due to the quantity and quality of well logs. The problem is also apparent in the regional explorations where well data are scarce or spatially far apart. In this study, several neural network types were tested for the purpose of solving the time to depth relations in field with relatively dense well network, selected in the NW part of the Sava Depression, Croatia. A distinctive lithological boundary was determined within wells and it's surface was interpreted from 3D seismic cube. Input data for the learning process were grid points with seismic two way time (TWT) expressed in ms and the absolute depth (Z) of the lithological borders determined from the well in part of grid points. Maps of selected borders were generated by neural prediction of time to depth relations of TWT values for each grid point. The validation of the approach was tested by comparing the values of surfaces generated by neural networks with ones by kriging and with values from wells which were subtracted from the dataset for learning. Multi-layer neural networks proved to be the most successful with the task of solving the time to depth relationships.

Keywords: *Neural networks, velocity modeling, 3D seismic, Sava Depression, Croatia.*

1. INTRODUCTION

Subsurface mapping in the domain of petroleum geology uses several inputs for obtaining maps with sufficient detail level for the task at hand, e.g. regional exploration for hydrocarbon accumulations with relatively low detail requirements or field development which requires high detail maps. End result of mapping procedure is the combination of well and seismic data. However, these two datasets are not in the same domain, well data represents depth in meters while seismic represents it in time (ms). Defining a valid relation of these two data sources is often a challenge, especially in areas and within fields which were explored in the early second part of the 20th century.

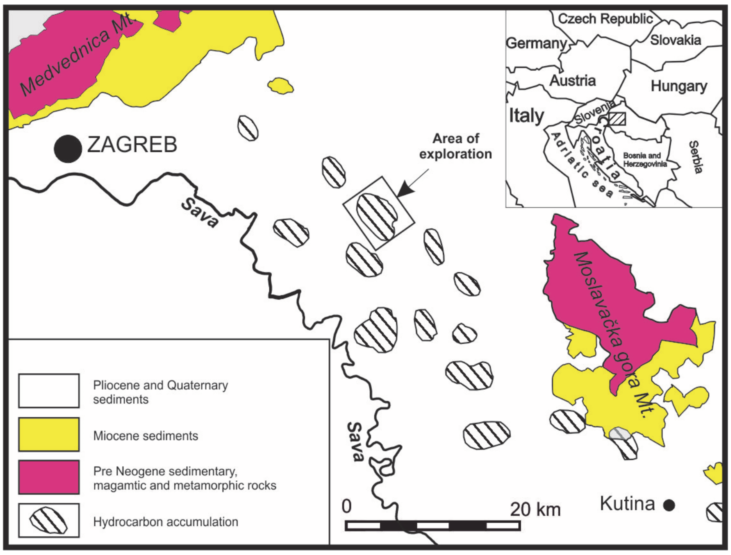

Figure 1: *Location of the area of exploration (modified after Velić et al., 2011)*

Well log data acquired in that time period lacked logs that are used for establishing time to depth relations (TDR) and often only consisted of conventional electric logs and determined E-log markers and borders. The second problem is the spatial distribution of the TDR or solving the TDR in the inter-well area. For all of these purposes, artificial neural networks (ANN) were used. An example is shown for solving the TDR for the deepest, least explored, E-log border Tg. Area of exploration is within an oil and gas field covered by a seismic 3D cube, located in the Sava Depression (**Figure 1**). Selection of the appropriate type of the ANN algorithm and network properties is crucial for obtaining TDR relations.

2. BASIC GEOLOGY SETTINGS

The ANN analysis will be limited only to the border of Neogene and Quaternary sediments and older pre-Neogene magmatic and metamorphic rocks. Neogene-Quarternary strata consists of heterogeneous lithology with frequent lateral changes (Malvić and Velić, 2011), thus making the TDR extremely complex. Middle Miocene Badenian and Sarmatian sediments are represented by coarse clastics, carbonates and marls while Upper Miocene intervals consist mainly of marls and sandstones with sporadic occurrences of breccias and biogenic limestones in the oldest parts of Pannonian. Youngest clastic interval of Pliocene, Pleistocene and Holocene age consists of poorly consolidate sands and clays, lignite and gravel in the youngest part. Thickness variation of the aforementioned interval is high due to the type of sedimentation and tectonic influence (Cvetković, 2013) and can have a high impact on the solving of the TDR.

3. ARTIFICIAL NEURAL NETWORKS

The basic architecture of neural networks consists of neurons that are organized into layers. A neuron is a basic element of a network that is mathematically presented as a point in space toward which signals are transmitted from surrounding neurons or inputs.

The value of a signal on the activity of a neuron is determined by a weight factor multiplied by a corresponding input signal. Total input signal is determined as a summation of all products of weight factor multiplied by the corresponding input signal given by

$$u_i = \sum_{j=1}^{n} (w_{ji} \cdot input_j) \tag{1}$$

where *n* represents the number of inputs for the neuron *i*. If the total input signal has a value more than the sensitivity threshold of a neuron, then it will have an output of maximum intensity. Alternatively, a neuron is inactive and has no output. Value of the output is given by

$$output_i = F(u_i \cdot t_i) \qquad (2)$$

where F represents the activation function and t_i, the targeted output value of neuron i. One can find a more detailed description of neural networks basics and methods in McCulloch and Pitts (1943), Rosenblatt (1958), and Anderson and Rosenfeld (1988).

For this analysis, several neural networks were used for comparison - multilayer perceptron (MLP) network and radial basis function (RBF) network. The MLP network is based on a backpropagation algorithm that has one or more hidden layers. The MLP is more successfully applied in classification and prediction problems (Rumelhart et al. 1986) and is the most often used neural network in solving geological problems. The RBF network is also a commonly used neural network but is more successfully and frequently applied in solving classification problems than in solving prediction problems. Neural networks have been successfully applied in petroleum geology problems such as determining reservoir properties (e.g., lithology and porosity) from well logs (Bhatt, 2002) and well-log correlation (Luthi and Bryant, 1997). In the Croatian part of the Pannonian Basin, only a few petroleum geology research projects have been performed. In these studies, clastic facies were determined from well logs (Malvić, 2006; Cvetković et al., 2009; Cvetković 2013) and porosity was predicted based on well and seismic data (Malvić and Prskalo, 2007).

4. METHODOLOGY

For the purpose of solving TDR relationship in the oil and gas field, a distinctive boundary between Neogene sediments and pre-Neogene magmatic and metamorphic rocks was selected. It's distinctive appearance on seismic and well logs (**Figure 2**) made it a good starting point for the research. Firstly the well log border Tg spatial coordinates were obtained. These consisted of well head northing and easting along with true vertical depth subsea (TVDSS).

Later, the Tg boundary was interpreted within the 3D cube for every 10th inline and xline from which the surface of the boundary was mapped with values in two way time (TWT) in ms.

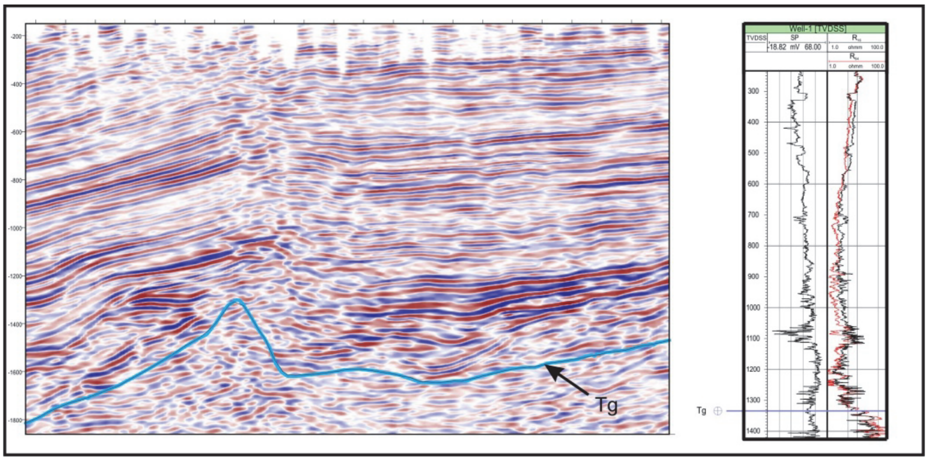

Figure 2: *Distinctive appearance of the Tg boundary on seismic profiles and well logs (SP left curve; R_{16} (black) and R_{64} red right curves).*

Dataset for training the neural networks consisted of four values of which three were defined as input and one as output variables (**Table 1**). A total of 36 values were used for ANN training process as this was the number of wells that drilled trough the Tg boundary.

Table 1: *Data formatting for ANN analysis with an example*

	Input variables			Output variable
Well	Northing (m)	Easting (m)	TWT (ms)	Depth (m)
Well 1	6378754,46	5065115,01	-1024,22	-1334,06

5. RESULTS

Several neural RBF and MLP networks with different properties (number of hidden layers, in the case of MPL, and with different number of neurons within hidden layers), were trained on the dataset. In general, MLP neural networks gave better results in training and selection which resulted in low error values (< 5%) while their RBF counterparts gave an average training error of 10% or more which can be at the depth of 2000 m an error of 400 m. Thus, only MLP neural networks were considered for the task of solving the TDR. Network with best properties was selected

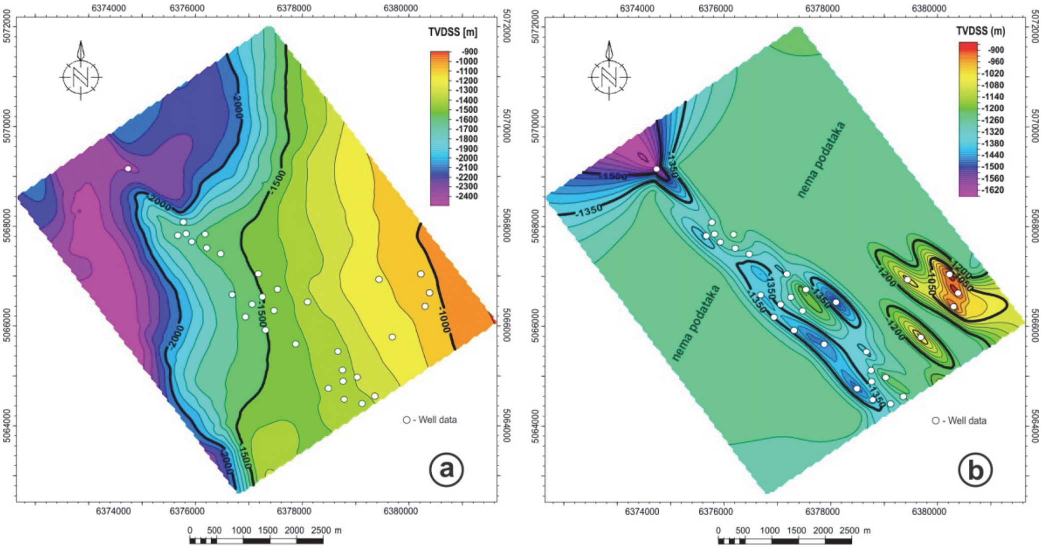

Figure 3: *a – map of E-log border Tg derived from neural network TDR analysis and seismic interpretation; b – map of E-log border Tg mapped by ordinary kriging of well tops values*

Trained neural network was used to predict the depth in meters from the TWT value of every node on the surface which was derived from seismic interpretation of the E-log border Tg. The surface showed high detail throughout the exploration area (**Figure 3a**). A much different structure on the resulting map (**Figure 3a**) was observed in comparison when only well data was used for mapping (**Figure 3b,** Malvić and Jović, 2012). Later, showed lots of uplifted structures which in fact resulted from small number of input wells which were placed unevenly across the field area.

6. CONCLUSIONS

For the purpose of solving TDR, MLP neural networks proved to be more successful than their RBF counterparts. Architecture of the RBF neural network with the presented task gave much larger training errors and the end result was high offset between TWT and depth values which cannot occur in the lithology that is observed within the selected oil and gas field. On the other hand, MLP neural networks showed much smaller training error and were successful in solving the TDR throughout the investigated area of the field. The end result was the possibility of more precise mapping of the area outside well coverage. Using of the neural networks for solving the TDR gave not only the distribution of velocities in a single verticle, but for a spatial distribution throughout the whole field area.

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8. LITERATURE

ANDERSON, J.A., ROSENFELD, E. (1988): Neurocomputing: Foundations of Research. MIT Press, Cambridge, 729 p.

BHATT, A. (2002): Reservoir properties from well logs using neural networks: doctoral dissertation, NTNU, Trondheim, 151 p.

CVETKOVIĆ, M. (2013): Naftnogeološki potencijal i litostratigrafska razradba trećega neogensko-kvartarnoga megaciklusa u Savskoj depresiji [Lithostratigraphic units of the third Neogene-Quarternary megacycle in the Sava Depression and their petroleum potential]. –PhD Thesis, University of Zagreb, Faculty of Mining, Geology and Petroleum Engineering, Zagreb, 175.

CVETKOVIĆ, M., VELIĆ, J., MALVIĆ, T. (2009): Application of neural networks in petroleum reservoir lithology and saturation prediction. Geologia Croatica, 62, 2, 115-121.

JACOBS, R.A. (1988): Increased rates of convergence through learning rate adaptation. Neural Networks , 1, 295-307.

LUTHI, S.M., BRYANT, I.D. (1997) Well-log correlation using a back-propagation neural network. Math. Geol., 29, 3,, 413-425.

MALVIĆ, T (2006) Clastic facies prediction using neural network (case study from Okoli field). Nafta, 57, 10, 415-431.

MALVIĆ, T. & JOVIĆ, G. (2012): Thickness maps of Neogene and Quaternary sediments in the Kloštar Field (Sava Depression, Croatia). Journal of Maps, 8, 3, 260-266.

MALVIĆ, T & PRSKALO, S (2007): Some benefits of the neural approach in porosity prediction (Case study from Beničanci field). Nafta, 58, 9, 455-467.

MALVIĆ, T & VELIĆ, J. (2011): Neogene Tectonics in Croatian Part of the Pannonian Basin and Reflectance in Hydrocarbon Accumulations. -In: SCHATTNER, U. (ed.): New Frontiers in Tectonic Research - At the Midst of Plate Convergence, InTech, Rijeka, 2011, 215-238.

McCULLOCH, W.S., PITTS, W. (1943): A logical calculus of ideas immanent in nervous activity. B. Math. Biol., 5, 4, 115-133.

ROSENBLATT, F. (1958): The perceptron: A probabilistic model for information storage and organization in the brain. Psychol. Rev., 65, 6, 386-408.

RUMELHART D.E., HINTON, G.E., WILLIAMS, R.J. (1986): Learning internal representations by error propagation. -In: RUMELHART, D.E., McCLELLAND, J.L. (ed.) Parallel Distributed Processing, Vol.1. MIT Press, Cambridge, 381-362.

VELIĆ, J., MALVIĆ, T., CVETKOVIĆ, M. (2011): Palinspastic reconstruction of synsedimentary tectonics of Neogene and Quaternary sediments in the Kloštar Field (Sava Depression, Pannonian Basin, Croatia). Zeitschrift der Deutschen Gesellschaft für Geowissenschaften, 162, 2, 193-203.