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HETEROGENOUS DISTRIBUTION OF INITIAL WATER SATURATION USING ARTIFICIAL NEURAL NETWORKS

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ABSTRACT

Artificial neuronal networks (ANNs) are rapidly becoming a very useful tool in the petroleum industry for predicting different evolution types for different parameters and use the human nervous system principles in creating the required prediction algorithm. Main objective of paper is to use a feedforward neural network to estimate the distribution of initial water saturation, as a small part of reservoir characterization in the presence of heterogeneities. It is very known that ANNs are complicated structures, take a long time in programing, are computer-time consuming and often require specialized aid in using them. Therefore, it will be an asset to know if reservoir heterogeneities can be pointed out with ANNs, or other prediction methods are indicated for these cases.

Keywords: modelling, artificial neural networks, water distribution

INTRODUCTION

Heterogeneities of all kinds affect hydrocarbon production on every reservoir. To have a better understanding of flow, both at a micro scale and at a macro scale, flow-property parameters must be known with sufficient accuracy and have a convenient scaling for the whole drainage area. Defining heterogeneities is rather complicated because the term is very comprehensive and can relate to about anything regarding the reservoir, like pore size and distribution, routine core analysis (RCA), fluid properties all the way to the field scale. The major drawdown consists in the reservoir dimensions being incomparable to the wells, but the latter provide crucial information regarding the reservoir, either by coring or by logging, furthermore, meeting the necessity to extrapolate the determined or measured values to the area between the wells. These extrapolations, however, are not fully accurate and no method will provide reliable data. Many papers in the literature discuss the efficiency of these methods, such as numerical and statistical ones, out of which we briefly mention [3, 5, 8].

Study [2] proposes an analytical model for the estimation of water saturation using capacitance-resistance modelling (CRM). Other study, like [9], [11] develop an empirical model to estimate water saturation distribution.

A new trend to predict heterogenous distribution of water saturation uses an artificial neural network algorithm. In his paper, [4] makes a comparison between artificial neural network models based on three layers and conventional statistical methods such as multiple linear regression. The results demonstrated the successful application of neural networks to predict water saturation. Other studies, such as [10], use a probabilistic neural network algorithm for predicting porosity and water saturation.

The misinterpretations regarding heterogeneities are the main cause for early water flooding and early gas cusping [12] if referring to the primary production stage, and the failures that occur in every other method of Increased Oil Recovery or Enhanced Oil Recovery (IOR/EOR) and can have a catastrophic effect on the reservoir integrity. Not mentioning the financial implications in such situations and not accounting for the reservoir heterogeneity can permanently damage the reservoir, leaving important volumes of unproduced oil trapped in the subsurface.

In this paper we analyze the distribution of the initial water saturation which is an important parameter from the RCA bulletin along porosity and absolute permeability. The purpose is to see if modern computational methods, such as ANNs are accurate enough to provide reliable data when extrapolating the target parameter to the area between the wells. From the start, we would like to mention the fact that ANNs require a substantial number of input data points, but its characteristic of self-adapting should help if the provided parameters are sufficiently precise. Data inputs are represented either by in-well measurements or mechanical cores sampled and analyzed from the wells which mean multiple measurements refer to the same parameter, the difference consisting in accuracy. Given the number of wells is very limited regarding ANN requirements, the self-adapting property plays a key role in the viability of initial water saturation distribution. In papers [6] and [7] both ANNs and other methods presented acceptable results in plotting the other two essential RCA parameters, porosity and absolute permeability but regardless of the method applied only estimations are obtained and the true distribution can never be known to the smallest detail.

BRIEF INTRODUCTION ON ANNs

According to [1], artificial neural network (ANN) is a data processing model inspired by biological systems and has many highly interconnected processing elements called *neurons*, which work in parallel to solve complex applications. In this study the authors developed three artificial neural networks models to estimate the water saturation heterogeneities for an abandoned oil reservoir. To develop this ANN model the Neural Network Toolbox from MATLAB was used. The neural network is feedforward type and is comprised of three layers (inputs, hidden and output layer), presented in figure 1. The input layer receives the two inputs values represented by well coordinates, the output layer usually it has one neuron represented by water saturation and hidden layer has 15 neurons, which is chosen using trial and error methods based on performance on artificial neural networks. Each neuron is connected to all neurons in the adjacent layers and receives the weight sum from all neurons from the previous layer.

The basic steps to develop neural networks are collecting data, eliminating errors, ANN type selection, choosing the training algorithm of neural networks and testing the neural network obtained.

The train algorithm is Levenberg-Marquardt method and the output from the last layer represents the network's predicted outputs – water saturation, and is calculated with the relation [6]:

$$y^{m}(t)=\sum_{j=1}^{nh} w_{j}\cdot f_{j}\left(net_{j}(t)\right), \tag{1}$$

$$net_{j}(t)=\sum_{i=1}^{nu} w_{j,i+1}\cdot u(t-i)+\sum_{i=1}^{ny} w_{j,nu+i+1}\cdot y(t-i) \tag{2}$$

where $y^m(t)$ denotes network output; $f_j(.)$ – output function of j node from hidden layer; $net_j(t)$ – output activation function associate j node of the hidden layer; nh – neurons number of the hidden layer; nu – neurons number associate with input $u(.)$; ny – neurons number associate with output $y(.)$; w_j – weight for the connection from the j hidden node and output node; $w_{j,i}$ – weight for the connection from the i input node and j output node; $y(t\text{-}i)$ – delay output process; $u(k\text{-}i)$ - input network.

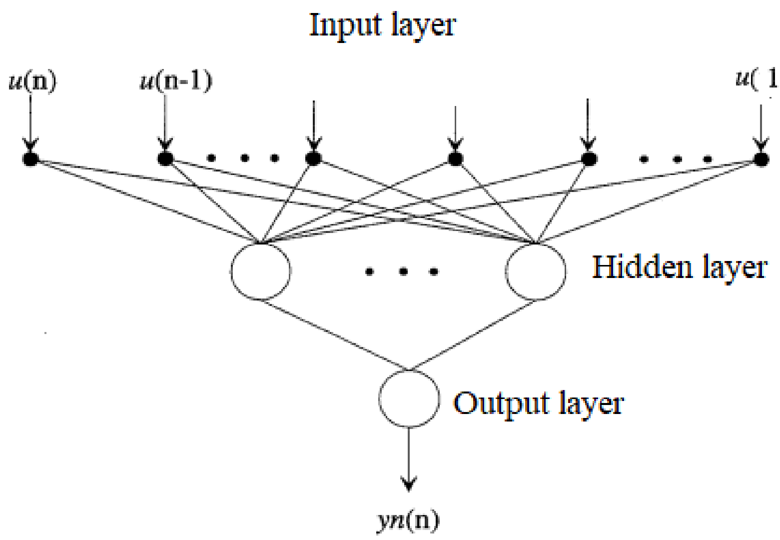

***Fig.1**. Feedforward neural network architecture.*

DATA USED

The available data comes from 20 wells and is represented by water saturation fraction, and geographical coordinates in ROMANIA STEREO 70 system. The date regarding the 20 well are presented in figure 2. From this 15 are used to training and five to test the accuracy of ANN model. It was making three scenarios base on test data. The first scenario uses four of the smallest and closest values for the initial water saturation, meant to be uniform, and as the fifth, the highest value, figure 3. The second scenario uses four of the highest and closest values, likewise, meant signify uniformity, and as the fifth, the smallest value, figure 4. The last scenario implies five values which have the maximum dispersion, figure 5.

Judging by the figures presented, the task for the ANN is to predict as accurately as possible the values which are possible to be found between the wells. We are expecting a high dropdown from the west to the other cardinal points and the maps should present a hump-like form with the apex in the western part that extends to a flatter region. The plots presented earlier were obtained after calculating the distribution of the initial water saturation for the area between the wells.

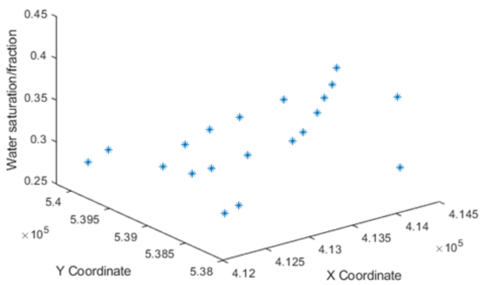

Fig. 2. *Input data.*

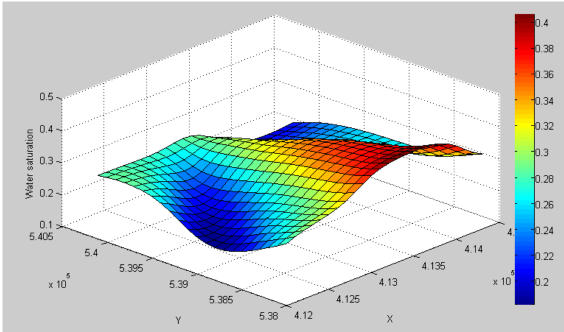

Fig.3. *Initial water saturation distribution, scenario 1*

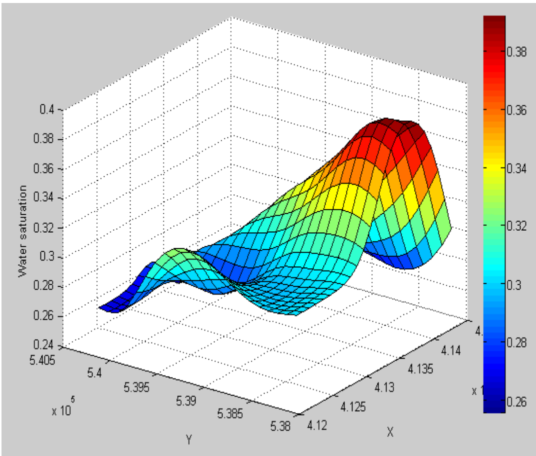

Fig 4. *Initial water saturation distribution, scenario 2.*

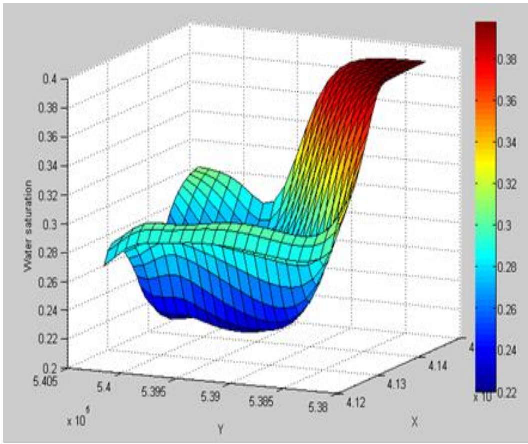

Fig 5. *Initial water saturation distribution, scenario 3.*

From the representations, we can see that a relatively smooth distribution is obtained if we consider the first case scenario. In this situation, heterogeneity is poorly pronounced, but values drop steeply from the west. Care should be taken if ANNs were to be instructed with low-homogenous values because from the representation we can observe a tendency of underestimation.

The second case scenario predicts well the dropdown of the values from the west but has difficulties to the southern part of the structure. The present anomaly is mainly argued by the fact that the western face of the grid intersects the representation in three points, all points having contrasting values. This concern is handled by either adding more data or by eliminating the outlying data point (the highest value from the southern side). Also, in this case scenario, we observe a slight tendency of overestimation.

The third case scenario shows almost a vertical dropdown for the initial water saturation from the western side but cannot handle the rest of the present values. In this situation, the ANN practically represented two homogenous zones: one with high values to the west and the other to rest of the interwell area.

This study is a continuation of the authors' research regarding the estimation of collector rock parameters. In papers [6] and [7] author presents an estimation of water saturation using polynomial regression methods and euro-fuzzy inference method. In figure 6 is presented a comparation between these three methods. It was concluded that artificial neural network method gave more satisfaction results.

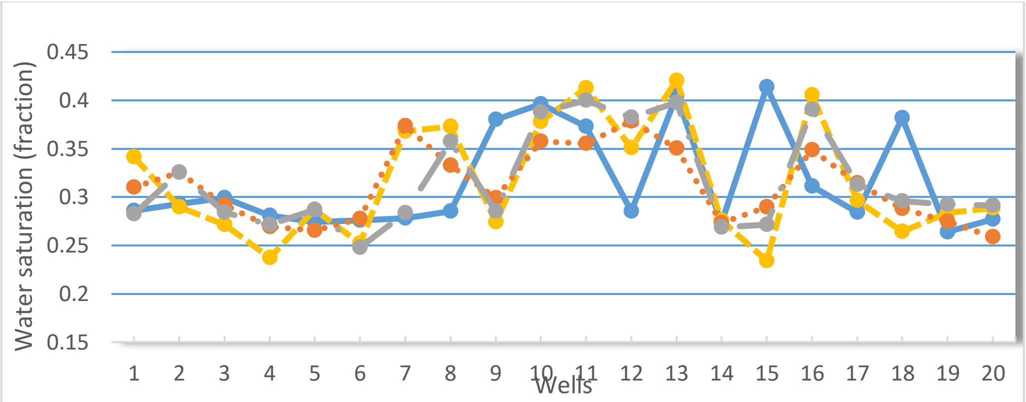

Fig. 6. *Comparation of the estimated initial water saturation (blue – real data, yellow – ANN, red- polynomial regression, gray – neuro fuzzy method)*

CONCLUSIONS

Heterogeneities can refer to many aspects, but this paper concentrated only on initial water saturation. Although many methods exist for plotting RCA parameters, we focused only on ANNs because they prove very useful in many fields of study, and they are self-adaptive. This method proved good overall efficiency just as in the case of porosity mapping.

The uses the artificial neural networks to predict water saturation distribution has many advantages over empirical model. The ANNs could use raw data as they are, without loss of information.

The best results which were obtained when plotting maps for initial water saturation had an ANN algorithm trained with the highest values along with one low value. Of course, our approach was limited by the number of values but as a general indication, we can conclude that the highest values along with as few as possible low values should be used as training data to obtain the most conclusive distribution maps.

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