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Full Length Article

Estimation of the non records logs from existing logs using artificial neural networks

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ABSTRACT

Finding the information of the hydrocarbon reservoirs from well logs is one of the main objectives of the engineers. But, missing the log records (due to many reasons such as broken instruments, unsuitable borehole and etc.) is a major challenge to achieve it. Prediction of the density and resistivity logs (R_t, DT and LLS) from the conventional wire-line logs in one of the Iranian southwest oil fields is the main purpose of this study. Multilayer neural network was applied to develop an intelligent predictive model for prediction of the logs. A total of 3000 data sets from 3 wells (A, B and C) of the studied field were used. Among them, the data of A, B and C wells were used to constructing and testing the model, respectively. To evaluate the performance of the model, the mean square error (MSE) and correlation coefficient (R^2) in the test data were calculated. A comparison between the MSE of the proposed model and recently intelligent models shows that the proposed model is more accurate than others. Acceptable accuracy and using conventional well logging data are the highlight advantages of the proposed intelligent model.

1. Introduction

Density and resistivity are two important parameters in reservoir evaluation and geophysical/geomechanical studies. Hence, the ultimate objective of reservoir evaluation studies by density and resistivity in the petroleum industry is to economically establish the existence of producible hydrocarbon reservoirs. Also, geophysical/geomechanical studies by using density and resistivity can be used to determine hydrocarbons presence, determination of fluid type-gas, oil, water, bitumen, computation of porosity, computation of water saturation and lithology [1,2]. These parameters could be determined from either laboratory methods or well logging operation. The laboratory methods are very expensive and time consuming. Since 1980s, geophysical well logging has been one of the key tools in hydrocarbon resource evaluation and management alike. Well logging is also considered as an integral part of formation evaluation that can provide great amount of data, which can be the best candidate to help in stages in developing reservoir static and dynamic models for efficient production and economic recovery [1]. But, it is quite common for the log records to be missing due to many reasons such as broken instruments, hole conditions, instrument failure, or loss of data due to inappropriate storage and incomplete logging [3,4]. This can result in the absence of some logging intervals or even an entire log type. Therefore, it is appeared that finding a new method for estimation of these parameters is necessary. For this purpose, many studies have been focused on prediction of the wire-line logs. Most of these studies have been tried to propose an intelligent model using artificial intelligence (AI) techniques. The artificial intelligence techniques have the remarkable ability to establish a complicated mapping between non-linearly linked input and output data [5].

In recent years, there has been an increasing interest in developing artificial neural network models for prediction of the density and resistivity logs from conventional wire-line logs in the world. A review of the published related studies is presented here.

In 2012, Masoudi et al. used Bayesian Network in identifying effective logs, i.e. feature selection for determining productive zones through oil wells. Due to the results, the ratio of Latero log Deep Resistivity (LLD) to Latero log Shallow Resistivity (LLS) and individually LLD are the most effective raw features for detecting productive zones through oil wells. Based on the results of the

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latter, porosity and water saturation are the most important extracted features for evaluating productive zones [6].

Bahrpeymaet al., [7] proposed a new fast fuzzy modelling method (FFMM) using Ink Drop Spread (IDS) and Center of Gravity (COG) operators to estimate missing log of density. For performance evaluation of the proposed model, they also estimated the density log using artificial neural network (ANN) and conventional fuzzy logic (FL). To predict the Sonic log (DT), density log (RHOB) and photoelectric log (PEF) and neutron log (NPHI) were used as input. Their results indicate that the accuracy of the proposed method is almost the same as the accuracy of ANN and TS-FIS (Takagi–Sugeno fuzzy inference system) methods but computational complexity, storage requirements and simplicity of the proposed method are much better.

Bahrpeyma et al., [8] employed active learning method (ALM) to estimate another missing log in hydrocarbon reservoirs, namely the density log. The regression and normalized mean squared error for estimating density log using ALM were equal to 0.9 and 0.042, respectively. The results, including errors and regression coefficients, proved that ALM was successful in processing the density estimation.

In this paper, by using artificial neural networks, it is tried to propose an intelligent predictive model to predict the density and resistivity wire-line logs from another conventional wire-line logs (R_{xo}, S_w, S_{xo}, NPHI, RHOB, R_{xo}, LLD, MSFL) in Mansouri oil field which is one of the most important Iranian southwest oil fields. Some advantages of this study include the following:

- The estimation technique is relatively simple, economical and quick.
- Inputs (depth, compressional wave velocity and density data) are available in most wells.
- Generally, well logs can provide a continuous record over the entire well; thus, using well log data as input can be estimated over whole of the well.
- In the ranges of the used data, the proposed model is intelligent.

2. Methodology

In this study, artificial neural networks (ANNs), which is one of the all techniques, was applied to develop an intelligent predictive model for prediction of the logs. ANNs, firstly introduced by McCulloch and Pitts [9], is a mathematical model of biological events in order to imitate the capability of biological neural structures with the purpose of designing an intelligent information processing system. An adaptive neural network is a network structure consisting of large number of elemental units, called neurons, organized in input, hidden, and output layers. Any neuron in the network is characterized by some features such as input weights, a threshold, and an activation function. The adjusting weights connect the neurons in different layers, so that a particular input, according to a learning algorithm, leads to a specific target output [9,10]. Neural networks can solve problems which cannot be solved by means of common calculations and discover highly complex relationships between several variables. A neural network works as a learning process from provided information, trains the data to form certain patterns for each subject, then predicts targets with the output model. In petroleum engineering, these networks are used when there is not enough data for interpretation [11,12].

Multi Layer Perceptron (MLP) network is one the common ANNs that may consist of one or more hidden layers and the input of each hidden or output layer is an inner product of the outputs of a previous layer and weights (Fig. 1). Each layer is composed of nodes and in the fully connected networks considered in this paper each node connects to every node in subsequent layers. In addition, the activation function of hidden layer(s) in MLPs is logistic sigmoid or hyperbolic tangent function that produces output [0, 1] and [−1, 1], respectively [13,14].

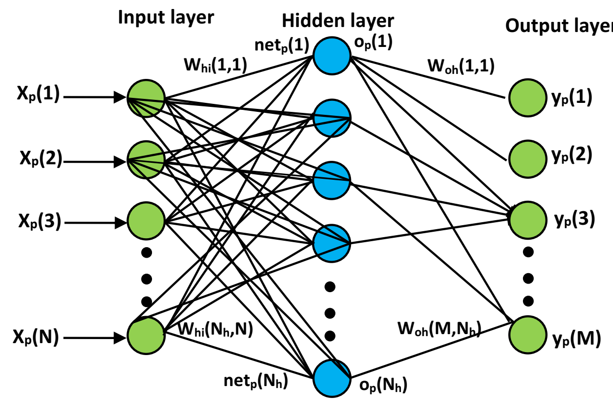

Figure 1. Architecture of MLP.

The input layer distributes the inputs to subsequent layers. Input nodes have linear activation functions and no thresholds. Each hidden unit node and each output node have thresholds associated with them in addition to the weights. The hidden unit nodes have nonlinear activation functions and the outputs have linear activation functions. Hence, each signal feeding into a node in a subsequent layer has the original input multiplied by a weight with a threshold added and then is passed through an activation function that may be linear or nonlinear (hidden units). Only three layer MLPs will be considered in this paper since these networks have been shown to approximate any continuous function. For the actual three-layer MLP, all of the inputs are also connected directly to all of the outputs. The training data consists of a set of N_v training patterns (x_p, t_p) where p represents the pattern number. In Fig. 1, x_p corresponds to the N-dimensional input vector of the pth training pattern and y_p corresponds to the M-dimensional output vector from the trained network for the pth pattern. For ease of notation and analysis, thresholds on hidden units and output units are handled by assigning the value of one to an augmented vector component denoted by $x_p(N+1)$. The output and input units have linear activations. The input to the jth hidden unit, $net_p(j)$, is expressed by:

$$net_p(j) = \sum_{k=1}^{N+1} W_{hi}(j,k).x_p(k) \quad 1 \leqslant j \leqslant N_h \tag{1}$$

With the output activation for the pth training pattern, $O_p(j)$, being expressed by:

$$O_p(j) = f(net_p(j)) \tag{2}$$

The nonlinear activation is typically chosen to be the sigmoidal function:

$$f(net_p(j)) = \frac{1}{1 + e^{-net_p(j)}} \tag{3}$$

In (1) and (2), the N input units are represented by the index k and w_{hi}(j,k) denotes the weights connecting the kth input unit to the jth hidden unit.

The overall performance of the MLP is measured by the mean square error (MSE) expressed by:

$$E = \frac{1}{N_v}\sum_{p=1}^{N_v} E_p = \frac{1}{N_v}\sum_{p=1}^{N_v}\sum_{i=1}^{M}[t_p(i) - y_p(i)]^2 \tag{4}$$

where

$$E_p = \sum_{i=1}^{M}[t_p(i) - y_p(i)]^2$$