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ORIGINAL ARTICLE

Application of Artificial Intelligent techniques on Photoelectric Factor (PEF) log prediction

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ABSTRACT

In this study, Artificial Neural Networks (ANNs) are used to predict Photoelectric Factor (PEF) log in one of the fracture reservoirs in Iran. For this purpose, the provided data for Sonic, Neutron Porosity, Depth, Conductivity and Bulk Density logs are used as inputs to the ANNs and PEF log is used as output. In order to consider the sensitivity analysis, following input conditions are considered: In first case, Sonic, Neutron Porosity and Depth logs are used as inputs to the network. In second case, Sonic, Neutron Porosity, Depth and Conductivity logs are used as inputs to the network. In third case, Sonic, Neutron Porosity, Depth, Conductivity, and Bulk Density logs are used as inputs to the network.

Obtained results indicate that using Bulk Density along with Sonic, Neutron Porosity, Depth, and Conductivity has better performance than the other cases with a mean squared error (MSE) and correlation coefficient (r) of 0.00860 and 94.67 %, respectively.

Keywords: *Artificial Neural Networks; Log Prediction, Photoelectric Factor.*

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INTRODUCTION

Log tools are essential in the evaluation of petrochemical properties of reservoir characterization. Parameters such as porosity, volume of shale, formation water saturation, lithology, fluid contacts and productivity zones are obtained from well logs. Sometimes because of bad well conditions, failure of instruments and etc, a complete set of data is not available and it seems to be necessary to predict the log responses [1].

Log prediction can help to reduce the costs of oil companies due to simulate the required data. Photoelectric Factor (PEF) log is essential for identification of lithology because of the direct correlation of photoelectric index with the type of lithology [2].

In the recent decade, ANNs have been increasingly applied to predict reservoir properties using well log data. The major reason for this rapid growth is their ability to approximate any function in an efficient way. In this study, Artificial Neural Networks (ANNs) are used to predict Photoelectric Factor (PEF) log in one of the fracture reservoirs in Iran.

ARTIFICIAL NEURAL NETWORKS

Neural networks are computational models of the biological brain. Like the brain, a neural network comprises a large number of interconnected neurons. Each neuron is capable of performing only simple computation [3]. Any how, the architecture of an artificial neuron is simpler than a biological neuron. ANNs are constructed in layer connects to one or more hidden layers where the factual processing is performance through weighted connections. Each neuron in the hidden layer joins to all neurons in the output layer. The results of the processing are acquired from the output layer. Learning in ANNs is achieved through particular training algorithms which are expanded in accordance with the learning laws, assumed to simulate the learning mechanisms of biological system [4]. However, as an assembly of neurons, a neural network can learn to perform complex tasks including pattern recognition, system identification, trend prediction and process control [3].

2.1. Multi-layer Perceptron

MLPs are perhaps the most common type of feedforward networks. Fig.1 shows an MLP which has three layers: an input layer, an output layer and a hidden layer.

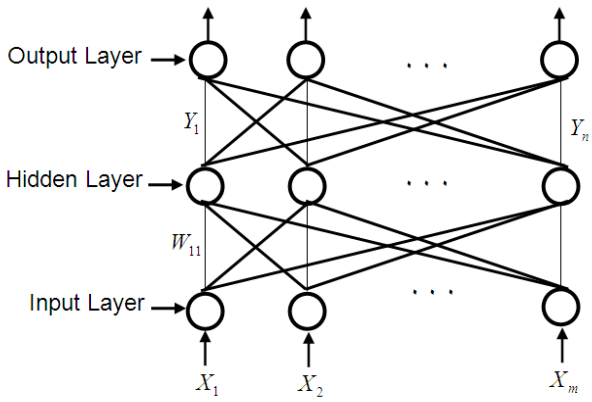

Figure 1.A multi-layer perceptron.

Neurons in input layer only act as buffers for distributing the input signals x_i to neurons in the hidden layer. Each neurons j (Fig. 2) in the hidden layer sums up its input signals x_i after weighting them with the strengths of the respective connections w_{ji} from the input layer and computes its output y_j as a function f of the sum, viz.

$$y_j = f\left(\sum w_{ji} x_i\right) \tag{1}$$

f can be a simple threshold function or a sigmoidal , hyperbolic tangent or redial basis function [6-9].

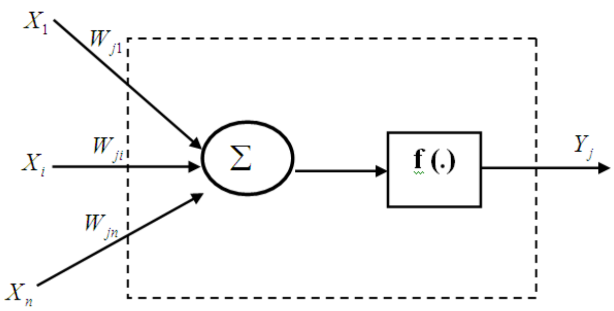

Figure2.Details of a neuron.

The output of neurons in the output layer is computed similarly the backpropagation algorithm, a gradient the descent algorithm, is the most commonly adopted MLP training algorithm. It gives the change Δw_{ji} the weight of a connection between neurons i and j as follows:

$$\Delta w_{ji} = \eta \delta_j x_i \tag{2}$$

Where η is a parameter called the learning rate and δ_j is a factor depending on whether neuron j is an input neuron or a hidden neuron. For output neurons,

$$\delta_j = \left(\frac{\partial f}{\partial net_j}\right)\left(y_j^{(t)} - y_j\right) \tag{3}$$

And for hidden neurons,

$$\delta_j = \left(\frac{\partial f}{\partial net_j}\right)\sum_q w_{qj}\delta_q \tag{4}$$

In Eq.3, net_j is the total weighted sum of input signals to neurons j and $y_j^{(t)}$ is the target output for neuron j.

As there are no target outputs for hidden neurons, in Eq.4, the difference between the target and actual output of a hidden neurons j is replaced by the weighted sum of the δ_q terms already obtained for neurons q connected to the output of j .

Thus, iteratively, beginning with the output layer, the δ term is computed for neurons in all layers and weight updates determined for all connections. The weight updating process can take place after the presentation of each training pattern (pattern-based training) or after the presentation of the whole set of training patterns (batch training). In either case, a training epoch is said to have been completed when all training patterns have been presented once to the MLP.

For all but the most trivial problems, several epochs are required for the MLP to be properly trained.

A commonly adopted method to speed up the training is to add a (momentum) term to Eq.2 which effectively lets the previous weight change influence the new weight change, viz:

$$\Delta w_{ji}(l+1) = \eta \delta_j x_i + \mu \Delta w_{ji}(l) \tag{5}$$

Where $\Delta w_{ji}(l+1)$ and $\Delta w_{ji}(l)$ are weight changes in epochs $(l+1)$ and (l) respectively and μ is the momentum coefficient [5-11].

PROBLEM DEFINITION AND RESULTS

In this study about 2300 data set for four wells located in Mansori filed with suitable distance from each other, were used to simulate the desired log (i.e. PEF). In order to consider the sensitivity analysis, following input conditions are considered: In first case, Sonic, Neutron Porosity and Depth logs are used as inputs to the network. In second case, Sonic, Neutron Porosity, Depth and Conductivity logs are used as inputs to the network. In third case, Sonic, Neutron Porosity, Depth, Conductivity, and Bulk Density logs are used as inputs to the network.

An approach that is used for scaling network inputs and outputs is to normalize the mean and standard deviation of the data set. It normalizes the inputs and outputs in the interval (0,1). in this study, the data set was divided randomly into two groups: training (70% of all data) and testing (30% of all data). The network was trained using the training set data. The actual output of the training set data was used to develop the weights in the network. At the established intervals, the test set was used to evaluate the predictive ability of the trained network. Training continued as long as the computed error between the actual and predicted outputs for the test set was decreased. The verification set is used to evaluate the accuracy of the newly trained network by providing the network a set of data it has never seen. There is possibility of using the current network weights or using the best network weights saved during a genetically training trial run. During the testing, the learning is turned off and the chosen data set is fed through the network. The network output is collected and a report is then generated showing the testing results. To aim this purpose, a code was developed in MATLAB 2010 (Math Works, Natick, MA). In order to determine the optimal network structure for each case, various network architectures were designed; the number of neuron and hidden layer and transfer functions in the hidden layer/output layer were changed. Eventually, logistic sigmoid transfer function for both hidden layers, and linear transfer function for output layer were found to be the best configuration for all proposed cases.

The performance of the models are accomplished by using well known statistical indices including: mean absolute percentage error (MAPE) and correlation coefficient (r).

Table 1 shows the performance of optimal trained networks for all considered cases.

As it can be seen in these tables, the best model has Mean Squared Error (MSE) and correlation coefficient (r) of 0.00860 and 94.67 % on testing period, respectively.

Figures 4 to 6 show the comparison of predicted values of PEF log with measured values on testing data for all cases.

Table 1. Training and testing errors of optimal trained networks for all cases.

#	Neuron in first hidden layer	Neurons in second hidden layer Transfer function	Training	Testing	
			MSE	MSE	r
ANN-I	18	9	0.00177	0.03387	91.84
ANN-II	17	8	0.00177	0.02158	92.22
ANN-IIII	15	6	0.00174	0.00860	94.67

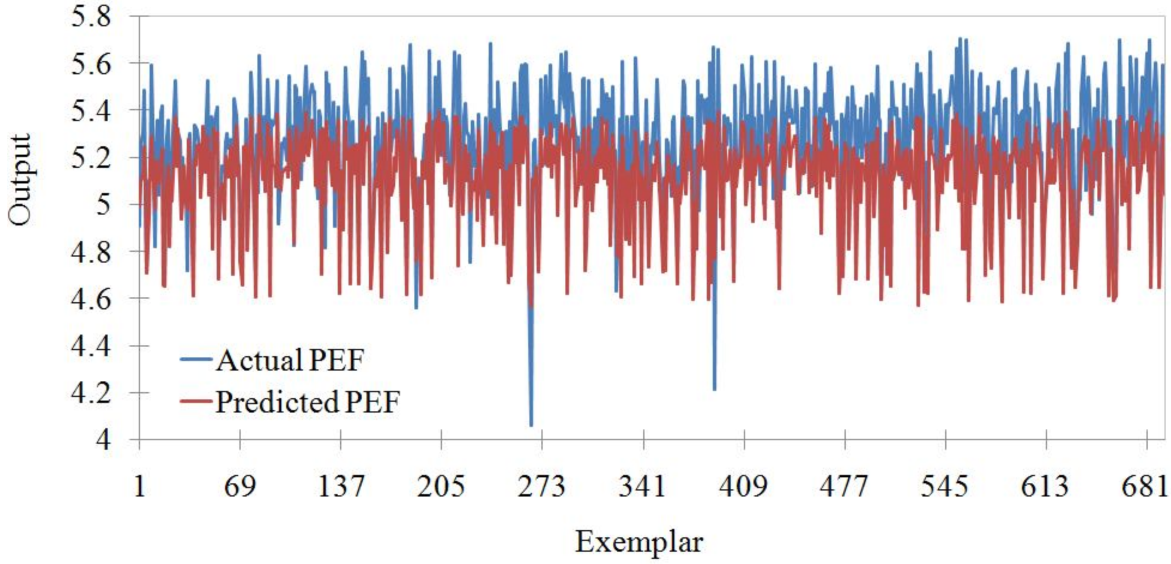

Figure 4. Comparison of predicted values with measured values on testing data for first case.

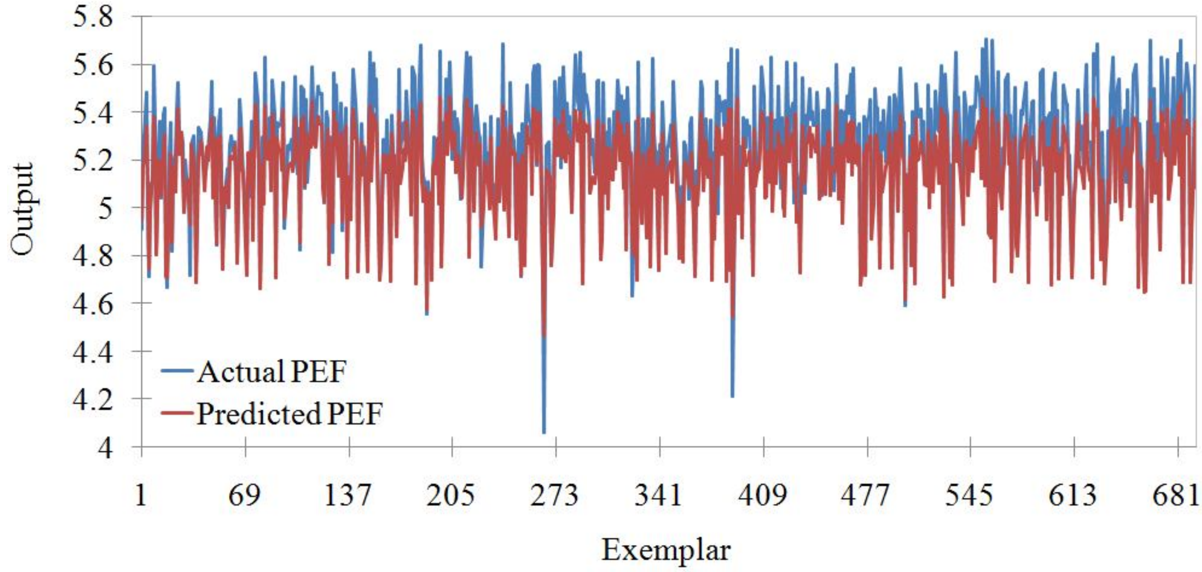

Figure 5. Comparison of predicted values with measured values on testing data for second case.

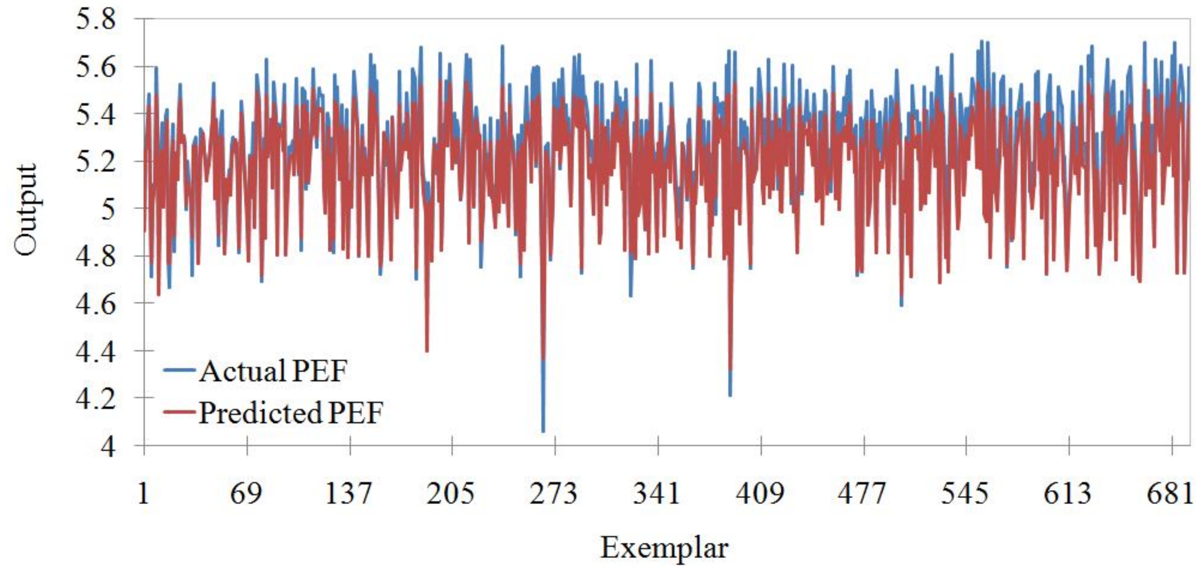

Figure 6. Comparison of predicted values with measured values on testing data for third case.

CONCLUSION

Numerous research efforts have been devoted to consider the accuracy of log prediction through ANNs. In this paper, the collected data for four wells located in Mansori filed with suitable distance from each other, were used to simulate PEF log. In order to consider the sensitivity analysis, following input conditions are considered: In first case, Sonic, Neutron Porosity and Depth logs are used as inputs to the network. In second case, Sonic, Neutron Porosity, Depth and Conductivity logs are used as inputs to the network. In third case, Sonic, Neutron Porosity, Depth, Conductivity, and Bulk Density logs are used as inputs to the network. Obtained results indicate that using that using Bulk Density along with Sonic, Neutron Porosity, Depth, and Conductivity has better performance than the other cases.

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