International Journal of Scientific Engineering and Applied Science (IJSEAS) - Volume-1, Issue-9, December 2015
ISSN: 2395-3470
www.ijseas.com

Studying the Capabilities of Two Neural Network Models in Optimization of Hydrocarbon Reservoir Management

Payam Parvasi[1], Javad Ghiasi-Freez[2], Amir Hatampour[1]
[1] Islamic Azad University of Dashtestan, Borazjan, Iran
[2] Iranian Central Oil Fields Company, National Iranian Oil Company (NIOC), Tehran, Iran

Abstract

Porosity is one of the most significant parameters of hydrocarbon reservoirs describing the quality of reservoirs rocks. It is one of the most crucial characteristics that need to be predicted for evaluation of reservoirs. The conventional methods for porosity determination are core analysis and well test technique. These methods are however very expensive and time-consuming tasks. One of the comparatively inexpensive and readily available sources of inferring porosity is nuclear magnetic resonance (NMR) log. The aim of this paper is to present an application of two machine learning methodologies, which are christened general regression neural network (GRNN) and back-propagation neural network (BPNN), for prediction of NMR porosity using well log data and intelligent models. Available data of three was considered for training and testing the networks. Verification process was also performed by one remaining well. Obtained results have shown that the overall correlation coefficients between predicted and measured porosity of GRNN and back-propagation are 0.93 and 0.91, respectively. In addition, in terms of accuracy, the GRNN technique has resulted in a RMS error reduction relative to that of the BPNN method. Hence, it can be concluded that GRNN is a better and more accurate method compared to BPNN in prediction of porosity.

Keywords: *Porosity, Well log data, General regression neural network, Back-propagation neural network.*

1. Introduction

Porosity is a key variable in characterization of reservoir and determination of flow patterns for optimizing the production. Reliable prediction of porosity is also crucial for evaluating the hydrocarbon accumulations as well as mapping the potential pressure seals. Several relationships have been offered which can relate porosity to wireline readings, such as the sonic transit time and density logs. However, the conversion from density and transit time to equivalent porosity values is not trivial. The common conversion formulas contain terms and factors that depend on the individual location and lithology, e.g. clay content, pore-fluid type, grain density and grain transit time. In the most cases, all of these individual factors must be determined from rock sample analysis. Hence, porosity is generally obtained either from core samples or well test techniques. The well testing and coring methods are however very expensive and time-consuming (Bhatt, 2002). This is the reason why well log data is usually used as an alternative approach for porosity determination. In addition, in a typical oil or gas field almost all wells are logged using various tools to measure geophysical parameters, while both well test and core data are available only for a few wells (Tiab and Donaldson, 2004). The log interpretation process implies the solution for geophysical problems because all the available data are combined to relate log measurement and the petrophysical parameters. Several log interpretation techniques have been used to detect hydrocarbon-bearing zones and to estimate their properties (Bassioni, 1994; Huenges et al., 1997; Doveton, 2000; Verga and Viberti, 2002). Alternatively, neural networks have been increasingly applied to predict reservoir properties using well log data (Mohaghegh et al., 1996; Aminian et al., 2000). Previous investigations (Artun et al., 2005; Rolon et al., 2009) have revealed that neural network is a proper tool for identifying the complex relationship among permeability, porosity, fluid saturations, lithology and well log data. General Regression Neural Network (GRNN) is a one-pass learning algorithm with a highly parallel structure (Artun et al., 2005). This method is a modification to probabilistic neural network which has been successfully used in many engineering applications.

Huang and Williamson (1994) described GRNN as an easy-to-implement tool, which has efficient training capabilities, and the ability to handle in complete patterns. GRNN is known to be particularly useful in approximating continuous functions. It is also able to have a multidimensional input, and can be easily fitted to multidimensional surfaces (Rolon et al., 2009). Since GRNN has been used for the prediction of petrophysical parameters in the limited number of cases, the aim of this paper is to present the application of this method in prediction of porosity using well logs. In this way, Burgan reservoir in the south of Iran is considered as a case study. In addition, to make a good comparison, performance of GRNN is compared with that of back-propagation neural network (BPNN). BPNN is another suitable machine learning methodology usually recognised for its prediction capabilities and ability to generalise well on a wide variety of problems (Cybenko, 1989).

2. Data Preparation

The main aim of this study is to predict porosity of a carbonate reservoir using well logs and corresponding NMR porosity. As a matter of fact, the well logs data are considered as inputs, whereas NMR porosity is taken as the output of the networks. Digitized well logs of this study are consisted of sonic log (DT), gamma ray log (GR) and density log (RHOB). Table 1 gives a correlation matrix showing relationships of different logs with NMR porosity. For the present study, a total number of 400 well logs and NMR porosity were obtained from 4 well drilled in a carbonate reservoir. Among these, one well containing 100 data was considered for validation of networks and remaining wells were used for training and testing the networks. In view of the requirements of the GRNN and BPNN computation algorithms, the data of the input and output variables were normalised to an interval by transformation process. Data pre-processing refers to analysing and transforming the input and output variables to minimize noise, highlight important relationships, detect trends, and flatten distribution of the variables to assist the networks in learning the relevant patterns. So, the input and output data must be scaled between the upper and lower bounds of transfer functions (usually between 0 and 1 or -1 and 1). In the present study, normalization of data (inputs and outputs) was done for the range of (-1, 1). In addition, the leave-one-out (LOO) cross-validation of the whole training set was used to adjust the associated parameters of the networks (Liu et al., 2006).

Table 1: Correlation matrix of input logs with porosity

	DT	GR	RHOB	Porosity
DT	1.000			
GR	.699	1.000		
RHOB	.601	-.333	1.000	
Porosity	0.831	0.734	-0.635	1.000

3. Prediction of NMR Porosity Using GRNN

Two wells containing 200 data were considered for training and one well (contains 100 data) was used for testing step. Root mean square error (RMSE) and correlation coefficient (R) are used to evaluate the effectiveness of each network. The Root mean square error (RMSE) is calculated using Eq. (1).

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{n}} \quad (1)$$

Where y_i is the measured value, $\hat{y}_i$ denotes the predicted value, and n stands for the number of samples. RMSE indicates the discrepancy between the measured and predicted values. The lowest the RMSE, the more accurate the prediction. Furthermore, the correlation coefficient, R, is given by:

$$R = \sqrt{1 - \frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{n} y_i^2 - \frac{\sum_{i=1}^{n}\hat{y}_i^2}{n}}} \quad (2)$$

Where R represents the percentage of the initial uncertainty explained by the model. The best fitting between measured and predicted values, which is unlikely to occur, would have RMSE=0 and R=1. Regarding to these two criteria, GRNN was trained by different smooth factors (SF) and the best SF was found as 0.24. Fig. 1 is a representation showing the best value of SF obtained regarding the RMSE of training dataset. Showing in Fig. 1, the optimum smooth factor (SF) was selected as 0.24 according to the least RMSE of training dataset.

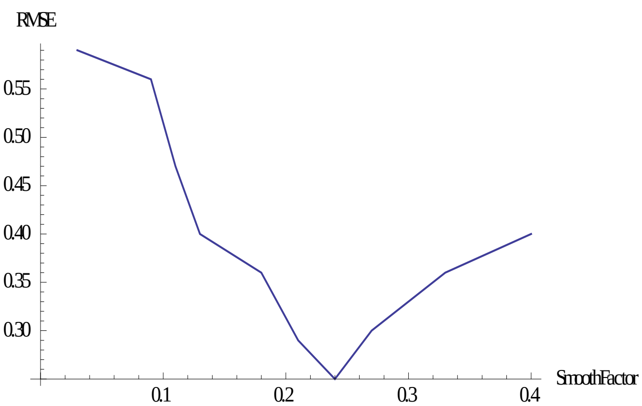

Fig. 1. Selection of SF using trial and error method in training step

Constructed GRNN of current study was a three layers network: input layer with 3 neurons (DT, GR and RHOB), hidden layer containing 200 neurons (i.e. number of training samples) and radial basic activation function and output layer with 1 neurons (i.e. Porosity) and linear activation function. Fig. 2 compares the measured and predicted porosity obtained in testing step. Highlighting in Fig. 2, constructed GRNN is able to properly predict the variation of porosity with correlation coefficient of 0.93. As a matter of fact, a closely followed pattern of variation shown by the measured and predicted NMR porosity suggests a good-fit of porosity.

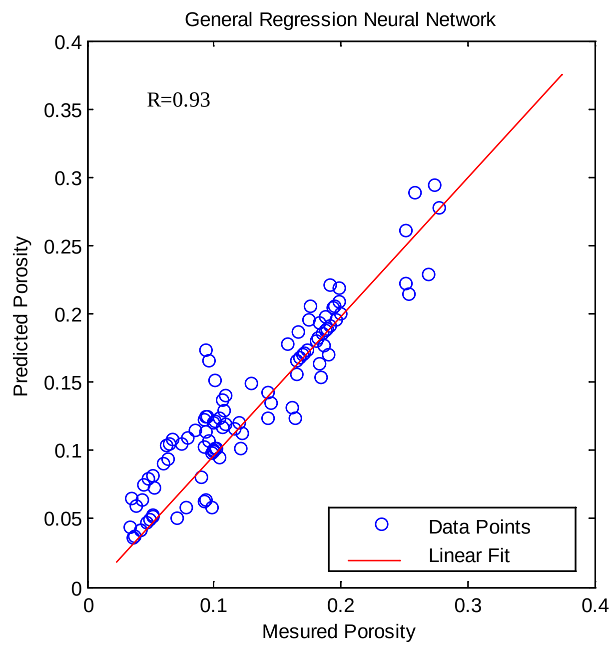

Fig. 2. Relationship between measured and predicted porosity obtained by GRNN

Fig. 3 shows another representing of GRNN ability in prediction of NMR porosity. As seen in Fig. 3, there is a good agreement between the measured and predicted NMR porosity of GRNN. Regardless of how great the prediction of GRNN is, another suitable method must be taken into account to make a good comparison.

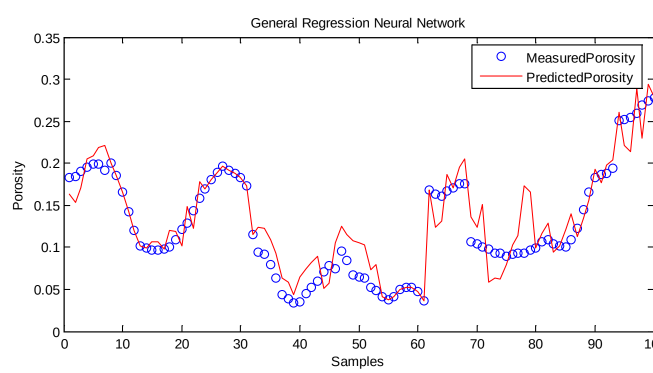

Fig. 3. Performance of GRNN in prediction of porosity

4. Prediction of NMR Porosity Using BPNN

Back-propagation neural network (BPNN) is usually recognized for its prediction capabilities and ability

International Journal of Scientific Engineering and Applied Science (IJSEAS) - Volume-1, Issue-9, December 2015
ISSN: 2395-3470
www.ijseas.com

to generalise well on a wide variety of problems. During the training, the network tries to match the outputs with the desired target values. Learning starts with the assignment of random weights. The output is then calculated and the error is estimated. This error is used to update the weights until the stopping criterion is reached. It should be noted that the stopping criteria is usually the average error of epoch. The optimal network of current study is a multilayer perceptron [Hornik, 1989; Haykin, 1994; Noori et al., 2010) which has one input layer including three inputs (i.e. DT, GR, and RHOB) and one hidden layers with 6 neurons and sigmoid activation function. The output layer has one neuron (i.e. porosity) with linear activation function (purelin) without any bias. Training function in this network is automated Bayesian Regularization algorithm (trainbr) used to avoid over-fitting. The constructed network, in this regard, employs approximately 35 parameters out of the 50 total weights and biases in the 3-6-1 network. In the present case, the algorithm was stopped in 158 epochs when its learning rate was 0.5. Obtained BPNN (3 neurons in input layer, 6 neurons in hidden layer and 1 neuron in output layer) was able to properly fit to the porosity data. Fig. 4 and 5 represent the performed work of BPNN in prediction of NMR porosity.

Demonstrating in Fig. 4 and 5, BPNN appropriately predicts the reservoir porosity. However, this prediction obtained by BPNN is not as good as that of the GRNN. Hence, BPNN can be considered as the second option after GRNN for prediction of NMR porosity. For further clarification, efficiency of these two networks is tested in subsequent validation step.

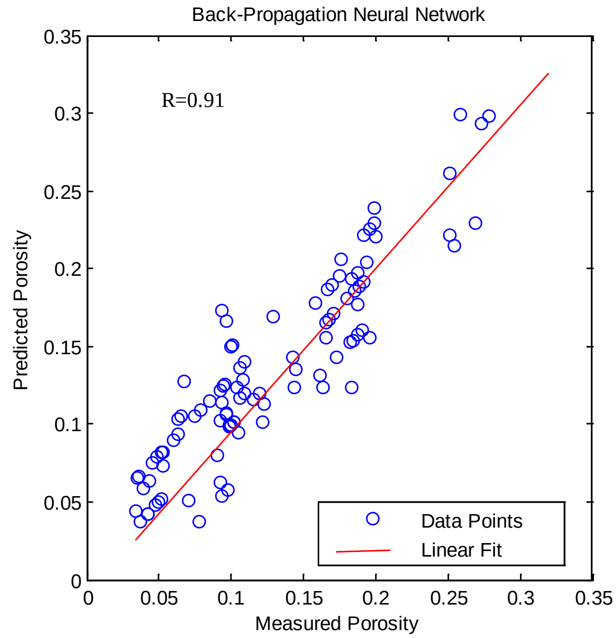

Fig. 4. Relationship between measured and predicted porosity obtained by BPNN

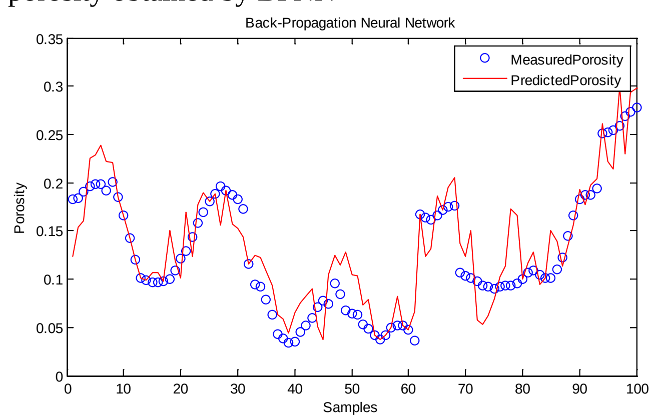

Fig. 5. Performance of BPNN in prediction of porosity

5. Verification

To show the efficiency of each network in validation step, one well including 100 data was used. Fig. 6 shows the ability of each network in prediction process of unseen data.

From Fig. 6, it can be concluded that GRNN is a better and more accurate method compared to BPNN in prediction of porosity.

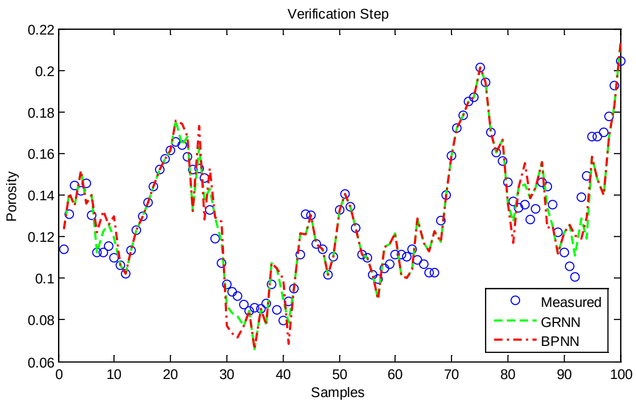

Fig. 6: Comparing the efficiency of each network in prediction of unseen data

Table 2: Comparing the performance of GRNN and BPNN methods in training and testing steps

Model	R (Train)	R(Test)	RMSE (Train)	RMSE (Test)
BPNN	0.998	0.91	0.16	0.45
GRNN	0.998	0.93	0. 16	0.25

6. Discussion

In this study, applications of two neural networks in prediction of NMR porosity were demonstrated. In fact, there was a comparison between the efficiency of a general regression neural network (GRNN) with that of a back-propagation neural network (BPNN). It was clearly shown that the GRNN presents an overall better performance over the BPNN in terms of RMSE in training and testing process (Table 2).
According to this table, the RMSE of GRNN is less than that of the BPNN. In addition, the GRNN takes a considerably less time for prediction compared with that of the BPNN. GRNN was also a more precise method in validation step.

6. Conclusion

Porosity is by far one of the most significant petrophysical parameters playing important role in reservoirs development, production and estimation.
This parameter describes the quality of reservoirs rocks in bearing fluid. In this paper, an application of GRNN and BPNN methods in prediction of porosity of four wells located in Burgan reservoir was tested and presented. It has been found that the GRNN is a faster and more accurate method in terms of relative RMSE of two methods (Table 2). Moreover, GRNN requires a small fraction of the computational time used by BPNN to present a better prediction.

Acknowledgments

The authors would like to appreciate Islamic Azad University of Dashtestan for providing the technical and financial supports of this research.

References

Bhatt, A. 2002. Reservoir properties from well logs using neural networks. A dissertation for the partial fulfillment of requirements for the degree of PhD at the Department of Petroleum Engineering and Applied Geophysics, Norwegian University of Science and Technology.

Tiab, D., and Donaldsson, E.C. 2004. Petrophysics, theory and practice of measuring reservoir rock and fluid properties. Gulf Publishing Co

Bassiouni, Z., 1994. Theory, measurement, and interpretation of well logs, vol. 4. SPE Textbook Series, Richardson, TX, 372 pp.

Huenges, E., Bqcker, C., Lippmann, E., Lauterjung, J., Kern, H., 1997. Seismic velocity, density, thermal conductivity and heat production of cores from the KTB pilot hole. Geophysical Research Letters 24 (3), 345– 348.

Doveton, J.H., 2000. Geologic log analysis using computer methods. AAPG Computer Applications in Geology, vol. 2. The American Association of Petroleum Geologist, Tulsa, OK.

Verga, F., Viberti, D., 2002. Uncertainty evaluation in well logging: analytical or numerical approach. SPWLA 43rd Annual Logging Symposium, Oiso, Japan

Mohaghegh S., Ameri S., and Aminian K. 1996. A methodological approach for reservoir heterogeneity characterization using artificial neural networks. Journal of Petroleum Science and Engineering. 16, 263–274.

Aminian K., Bilgesu H.I., Ameri S., and Gil E. 2000. Improving the simulation of waterflood performance with the use of neural networks. SPE 65630, Proceeding of SPE Eastern Regional Conference, October.

Rolon, L. 2004. Developing Intelligent Synthetic Logs: Application to Upper Devonian Units in PA. MSc thesis, West Virginia University, Morgantown, West Virginia.

Artun, E., Mohaghegh, S., and Toro, J. 2005. Reservoir Characterization Using Intelligent Seismic Inversion. SPE98012, West Virginia University.

Rolon, L.F., Mohaghegh, S.D., Ameri, S., Gaskari, R., McDaniel, B., 2009. Using artificial neural networks to generate synthetic well logs. Journal of Natural Gas Science and Engineering 2 (1), 2–23.

Cybenko G. 1989. Approximation by superposition of a sigmoidal function. Mathematical Control Signals System, 2: 303-14.

Liu H, Yao X, Zhang R, Liu M, Hu Z, and Fan B. 2006. The accurate QSPR models to predict the bio-concentration factors of nonionic organic compounds based on the heuristic method and support vector machine, Chemosphere 63, 722–733

Specht DF. 1991. A General Regression Neural Network. IEEE Transactions of Neural Networks 2(6):568-576

Hornik K, Stinchcombe M, and White H. 1989. Multilayer feed forward networks are universal approximators. Neural Network, 2: 359-66

Haykin S .1994. Neural networks: A comprehensive foundation (2nd Ed.). New York: Macmillan

Noori R, Khakpour A, Omidvar B, and Farokhnia A. 2010. Comparison of ANN and principal component analysis-multivariate linear regression models for predicting the river flow based on developed discrepancy ratio statistic, Expert Systems with Applications 37, 5856-5862.

Payam Parvasi is currently assistant professor at Azad University (Dashtestan Branch). He gained his PhD on Chemical engineering from Shiraz University. His MSc degree is on Chemical engineering from Shiraz University. His BSc degree is on Chemical engineering from Kashan University of Technology. Parvasi's research interests are in modeling of chemical processes.
Javad Ghiasi-Freez is a petroleum geologist working on the importance and implementation of intelligent systems in reservoir characterization and geoscience. He holds an MSc in petroleum engineering from Shahrood University of Technology, Iran. Up to now, he has presented several articles related to integrated intelligent models in international periodicals and conferences. He is an active referee of several ISI journals. In addition, application of Image analysis and pattern recognition in geosciences is his interest.
Amir Hatampour holds a BS degree from the Petroleum University of Technology and a MS degree from Amirkabir University of Technology (Tehran Polytechnic), both in petroleum exploration engineering and is pursuing a PhD on intelligent reservoir characterization.