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Improving Performance of a Neural Network Model by Artificial Ant Colony Optimization for Predicting Permeability of Petroleum Reservoir Rocks

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Abstract: Over recent years, oil and gas exploration has been beloved due to extended needs for petroleum and energy sources. In this way, the capabilities of intelligent techniques are studied by researchers in different fields of petroleum industry and geosciences, whereas it seems that these techniques can improve the prediction accuracy of exploration and production of the hydrocarbon reservoir. The performance indices of the artificial models have proven to be better than the conventional linear and non-linear statistical models. Artificial intelligence models are extremely useful for reservoir characterization, which requires a high-accuracy prediction for a good exploitation of the oil and gas resources. The present paper introduces an optimized neural network (NN) for predicting permeability based on a relatively new swarm intelligent approach, named ant colony optimization. Ant colony optimization (ACO) is a relatively new computational intelligent approach, which was initially inspired by the observation of ants. The number of neurons in hidden layer, weights and bias are optimized in the proposed NN using the ACO. The data of a gas reservoir in the South Pars Gas Field of Iran was used for analyzing the accuracy of optimized NN in a real case study. Finally, to clarify the advantages of the optimized NN, its outcomes were compared with the results of a simple NN model, in which the aforementioned parameters were determined through a try-and-error process. The MSEs of the optimized and simple NN were equal to 7.95 md and 12.84 md, respectively, which correspond to the correlation coefficient (R) of 0.94 and 0.866, respectively.

Key words: Permeability · Well log · Reservoir characterization · Optimized neural network · Artificial ant colony optimization · South Pars Gas Field · Iran

INTRODUCTION

Permeability is the ability of a porous rock to transmit fluids, which has a great importance in reservoir characterization. This property is a dynamic flow property, depending on the statistics of the pore throat diameters and other textural properties [1, 2]. There are several ways to determine permeability: the best and oldest one is laboratory measurement, which is not only time-consuming but also very expensive. In addition, coring is not available in all wells and even in the whole depth of a reservoir. In the first decades of petroleum exploration, simple models, such as Kozeny-Carman, attempted to predict the permeability using the porosity and a single characteristic length such as the mean pore diameter, mean grain size, or specific surface area [3-5]. In addition, the relationship between rocks structural properties and permeability has been discussed [6]. Up to now, several parameters used to estimate permeability. For instance, the surface area of the pore space [7], capillary pressure [8], Nuclear Magnetic Resonance relaxation time [9], sonic transit time [10] and pore throat characteristics derived from image analysis of thin sections [11-13] are the most popular approaches for predicting this important reservoir property. The recent developments have been targeted to predict permeability from the well log data using artificial Neural Networks [14-18]. This tendency of researchers grows by every-day developments of computer's sciences in software programming and hardware technologies.

The motivation of the current study includes the quest of higher accuracy in the prediction of permeability when dealing with the neural network models. Therefore, the local searching capabilities of an ant colony algorithm were employed for indicating the optimal topological architecture and parameters of a back-propagation NN model.

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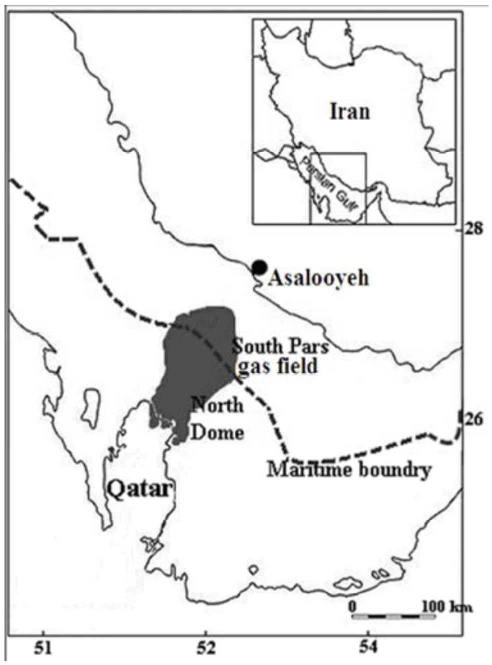

Fig. 1: Showing the location of South Pars gas Field

Designing an accurate and practical model through the intelligent systems can be saved millions of dollars in petroleum industries. Of course, a powerful model is seeking a strong database of inputs and outputs, which can be costly. However, the expenditure of the most expensive intelligent model may be less than the cost of coring procedure.

To magnify the significance of the proposed methodology the well log data of a real gas reservoir, South Pars gas field, were used for predicting permeability which is the most challenging parameter during reservoir characterization. South Pars gas field was discovered in 1990 by drilling an appraisal well in the Persian Gulf. The Iranian part of South Pars Gas Field, the world's largest non-associated gas accumulation, is located in the Persian Gulf, between Qatar and Iran at about 100 km from the Iranian shoreline. This gas reservoir has been shared between Iran and Qatar [19]. Thirty eight percent of its surface area belongs to Iran and the remains are extended in Qatari territorial waters. Figure 1 shows the location of South Pars gas Field and its Qatari part, named North Dome, in waters of the Persian Gulf.

Theory and Methodology

Neural Network: Multilayer perceptron (MLP) with back-propagation training is the most widely used neural network in the prediction and correlation problems. The important characteristic of the back-propagation neural network is that it learns to reproduce the output by discovering the hidden patterns contained within the data. Back-propagation neural network is a supervised learning method, which means that it requires a set of training data having the desired output for any given input. The network computes the difference between the calculated output and corresponding desired output from the training data set. The error is then propagated backward through the net and the weights are adjusted during a number of iterations. The training stops when the best approximations of desired values are calculated.

What Is the Artificial Ant Colony Optimization (ACO) Algorithm?: Ant life has attracted the attenuation of researchers due to its complex social behavior. One of the most amazing behaviors of ants is the ability to find shortest paths from a food source to their nest. Biologists had believed that this fact can be possible by splashing special liquid, called pheromones, in their path. The pheromone is an odorous chemical substance that ants can deposit in order to indicate some favorable path for other members of their colony. In fact, the probability for selecting a path is increases when the amount of pheromone increases in the path. Artificial ant colony optimization (ACO) is a relatively new computational intelligent approach, which was initially inspired by the observation of ants. [20] has formalized ACO into a meta-heuristics algorithm for solving the optimization problems. A meta-heuristics refers to a computer science branch, which selects a computational technique for optimizing a fitness function by improving a candidate solution.

The ACO algorithm consists of six components. These include the particles, a fitness evaluation unit, particle position, search velocity, vaporization and splashing. Each candidate solution in the problem space is called a particle. In another word, the particle in an artificial ACO plays the role of ants in the real word. The position and search velocity are the characteristics of each particle. The process in which an ACO can find the best solution was explained as below: Firstly, the values of particle position and search velocity for each particle are randomly indicated. The algorithm allows each particle to move through the problem space. Simultaneously, the algorithm saves a record from the particle's characteristics and evaluates the objective value of each particle. At the end of this step the particles with higher fitness were selected for the next generation of the colony. Such a procedure happens for the selected in another generation and it was continued until the chosen number of generations is achieved. Then, the position and search velocity of particles with the best fitness value were generalized to the environment. In fact, the fitness value shows the amount of pheromones in the path of particles. During the generations, the ACO uses the vaporization and splashing operators to avoid local minimum. Through the vaporization operator, the amount of pheromones is randomly decrease in the paths to avoid the trapping of the algorithm in local minima, while a splashing operator performs inversely. In the searching process of the ACO algorithm, the searching space will reduce gradually as the generation increases.

Why to Use the ACO for Optimizing the Parameters of Neural Network Model?: The architecture of a neural network has a functional impact on its performance. Number of neurons in the hidden layers, weights and bias of the network are the most important factors of a multi-layer neural network. On the other hand, the exploration space of the NN model is widespread and it is difficult to find the optimum answers for these requirements of the NN. The ACO is a new type of computational algorithm, which has been used extensively for a variety of optimization problems. It incorporates a remarkable ability for solving the non-smooth, non-continuous, non-differentiable ?tness functions. In addition, it is able to gain the global and local minima within a short computation time. Hence, this method is efficient in handling large and complex search spaces.

The most important weak point about the ACO algorithm is its slow searching close to the global minimum points of a problem; however, it is a powerful algorithm to find local minimum points. On the opposite hand, the NN models have a strange ability to find local minimum points but its ability to find global optimistic results is not as fast as the ACO. Therefore, the combination of these two models can perform accurate and find the optimum results in a short time. In fact, the ACO accelerates the training speed at the first stages of searching for the optimum.

Data Description: In this study, the well log data and corresponding core data of three wells were employed for training and examining the validation of the proposed method. Firstly, the data sets were processed and bad-hole intervals, in which the derivation between the caliper and bit-size logs is larger than 1.5 inch, were removed. To ensure the correct reading of well-log data against core permeability, a depth-matching procedure was carried out.Normalization of data is another task, which could be done for better prediction of outputs. In the training data, permeability range changes from 0.007 to 271 md.

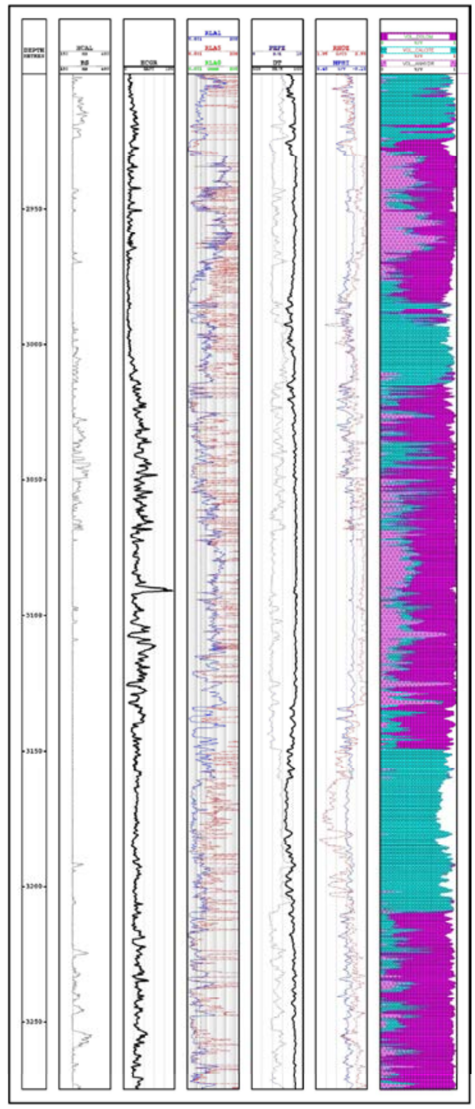

Fig. 1: A display of the used well log data

This wide range causes low performance of the model in permeability prediction; therefore, the normalized data have been used to enhance the performance of prediction. A total of 301 core samples were available for this research, among them 218 samples were from Well A and B (train wells) and 83 samples were used for validating purposes. The train and test wells should be located in a suitable distance from each other. In a suitable distance, the geological and petrophysical rock properties that affect the reservoir characteristics are consistent. The available well log data for this study were gamma ray (GR), sonic (DT), bulk density (RHOB), deep laterolog (LLD), photo electric factor (PEFZ) and corrected neutron porosity (NPHI). An example of the used well log data is shown in Figure 1.

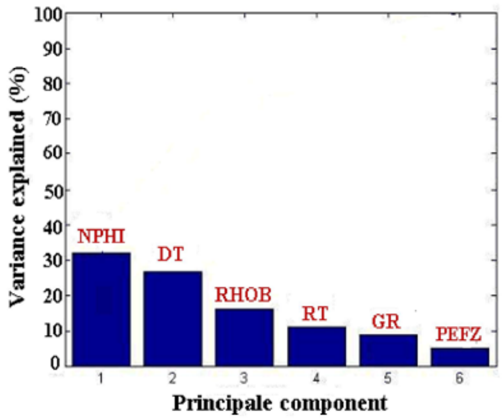

Fig. 2: Showing the importance of each well log for predicting permeability using the principal component analysis

A brief introduction of the used well log data is presented here. A GR log records the variation of natural radioactivity of formation around the borehole. This log is a useful tool for identifying shale and clay intervals because these lithologies are responsible for natural radioactivity. The sonic log has been found so effective in the determination of porosity and it is a standard tool for porosity estimation, fracture and lithology determination. The bulk density log determines the density of a rock as its title also says. This well logging device is used for analyzing the distribution of pore spaces with a rock. The density value of a rock can be converted to porosity whereas a porous formation has smaller density with respect to compacted one. Neutron porosity log used a radioactive source to bombard the formation with high energy particles called neutrons. As high energy neutrons collide with the various atoms of formation and fluids their energy starts to lose. The amount of decreased energy stated as porosity of the formation. As mentioned above, DT, RHOB, and NPHI are called porosity logs. Deep laterolog transfers electrical currents through a formation for measuring the resistivity of its fluid. This tool can be used for separating watery formations from oily ones. The PEFZ log is an advanced version of the density log, which used for identifying of lithology [21].

The inputs of the NN models could be chosen assuming the importance of each log on the permeability prediction. To examine the relative impact of the well log data on permeability, a principal component analysis was conducted. The principal component analysis (PCA) is a linear input dimension reduction technique that computes the largest eigenvectors of the covariance matrix of the feature set [22]. PCA selects the most expressive inputs related to eigenvectors with the largest eigen-values. Therefore, it can approximate the input set space by a linear subspace. Figure 2 obtained from the PCA analysis and shows the importance of each log for predicting permeability.

Clearly, among the well log data, NPHI with 30.2 %, DT with 27.1%, RHOB with 17.6%, RT with 13.3%, GR with 7.3% and PEFZ with 6.1% show the largest to smallest significance. Based on these values, NPHI, DT, RHOB and RT were selected as the inputs of the NN models, which are designed in this study.

Construction of the Optimized Neural Network by ACO: To recognize the optimum architecture of the NN, a fitness function should be introduced to the ACO. This fitness function must encompass the vital parameters of the NN, which are necessary to optimize. We have developed the fitness (objective) function of the i-th training sample as the mean square of the NN.

$$\text{Fitness}\ (X_i) = \text{MSE}\ (X_i) \tag{1}$$

To optimize this function through the ACO, a group of random particles is initiated and the ACO stats searching. During the searching, all the particles should be updated, until a new generation set of particles is produced. Then these new particles are used to search the global best position in the solution space. When the ACO algorithm is used for evolving weights and bias of neural network, every particle represents a set of weights and bias. The set that corresponded to the lowest MSE is chosen as the optimal architecture of the optimized NN. In a similar way, the ACO can be used for determining the optimum number of neurons in the hidden layer. In the current study, the parameters of the ACO were adjusted as below:

ACO was trained by 40 generations, followed by a BP training procedure. In the ACO, every initial particle is a set of weights generated at random in the range of [-1, 1]. The initial inertial weight of the ACO was chosen as 0.87. The acceleration constants, are two random numbers in the range of [0, 1], respectively. The maximum velocity assumed as 0.5 and the minimum velocity as-0.5. The initial velocities of the initial particles were generated randomly in the range of [0, 1]. After each iteration, the velocity was calculated. If it was larger or smaller than the maximum velocity or the minimum velocity, it would be reset to 0.5 or-0.5. The ACO population size is 200. The value of learning coefficient, 0.8 and momentum correction factor, 0.002, were used for the back-propagation training algorithm.

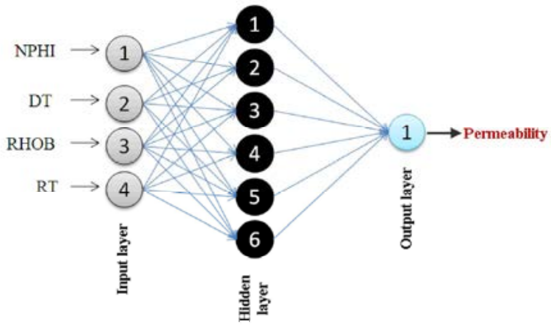

Fig. 3: Showing a schematic diagram of the simple NN model

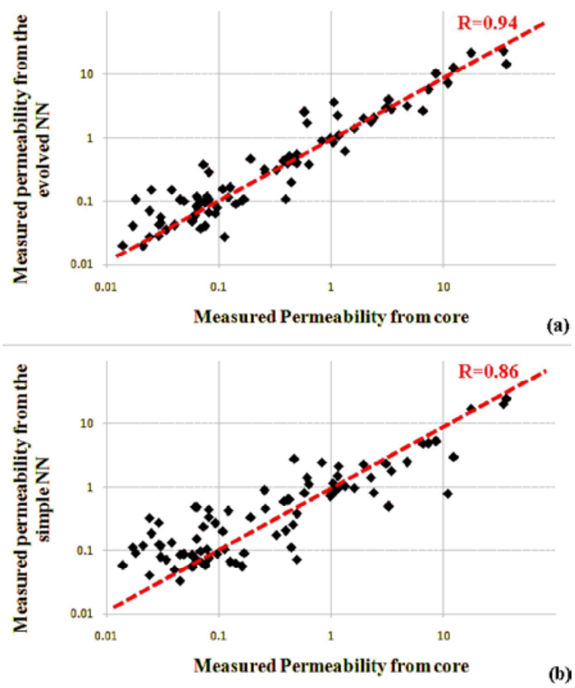

Fig. 4: Cross-plots show the correlation coefficient between the measured and predicted permeability using (a) the evolved NN, (b) the simple NN model

Comparison of the Optimized Neural Network with Simple NN Model: To analyze the advantages of optimized NN model, a simple multi-layer NN model was developed. The Levenberg-Marquardt training algorithm was used for randomly updating weights and bias values of the simple three-layered error back propagation algorithm. The hidden layers included six neurons. A schematic diagram of the used NN model was shown in Figure 3.

In the simple NN, the number of neurons was randomly assigned; however, it is necessary to determine the optimal number for this variable. This process is a time-consuming procedure through a trial-and error approach, which can be done by the ACO in a short time and without any effort. The ACO proved that the optimum number of neurons for hidden layer is 13.

The MSE between measured and predicted permeability using the optimized NN is 7.95 md, which corresponds to the correlation coefficient (R) of 0.94, while the MSE of simple three-layered is 12.84 which corresponds to the R of 0.86. Figure 4 shows a clear representation of the obtained correlation coefficients.

RESULTS AND DISCUSSION

Two NN models were employed to predict permeability values using the two paradigms but with different methodologies. In the first NN, the training parameters including weights, bias and number of neurons in hidden layer are adjusted using an ACO algorithm, while the second NN's parameters were randomly initiated.

A total of 303 data points were used to train two NN models. After training and adjusting the parameters of the optimized NN model through an ACO algorithm, the test data points were introduced to it. The results were in a very good agreement with the core data, which indicates that the ACO model could recognize the optimum architecture of the NN and this leads to a proper capturing of the relationship among inputs and outputs. Figure 5(a) shows a comparison between the real and predicted permeability by the optimized NN versus depth. As expected, the trend of measured permeability changes was followed by the optimized NN.

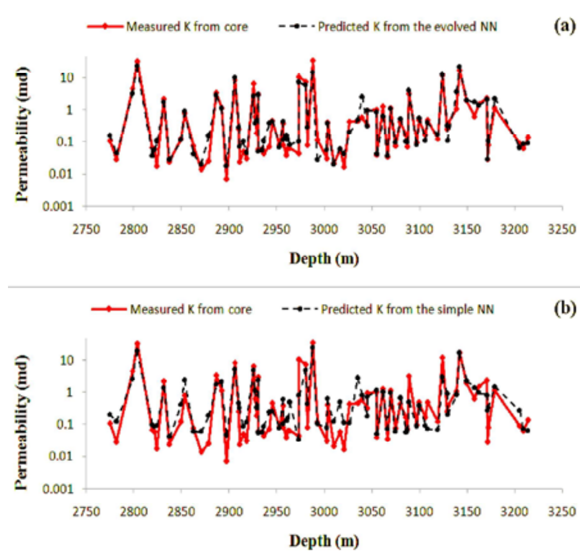

Fig. 5: Illustrating a comparison between measured and predicted permeability using (a) the evolved NN, (b) the simple NN versus depth. The word "K" is the representative of "permeability"

To illustrate the advantage of the optimized NN, a simple three layered NN was also trained through a similar data set of well logs and core data. However, the weights, bias and number of weight in the hidden layer were randomly assigned. Figure 5(b) shows the real and predicted permeability by simple NN. The result demonstrates that the optimized NN performed more accurate compared to the simple NN model. In the other words, the optimized NN results were much favorable to a petroleum geologist than those given by the simple NN.

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REFERENCES

1. Korvin, G., 1992. A percolation model for the permeability of kaolinite-bearing sandstones, Geophysical Transactions, 37(2-3): 177-209.
2. Kharrat, R., R. Mahdavi, M.H. Baghetpour and H. Shahab, 2009. Rock Type and Permeability Prediction of a Heterogeneous Carbonate Reservoir Using Artificial Neural Networks Based on Flow Zone Index. SPE., 120166: 18.
3. Berryman, J.G. and S.C. Blair, 1986. Use of digital image analysis to estimate fluid permeability of porous materials. Journal of Applied Physics., 60: 1930-1938.
4. Blair, S.C., P.A. Berge and J.G. Benyman, 1996. Using two-point correlation functions to characterize microgeomeny and estimate permeabilities of sandstones and porous glass. Journal of Geophysical Research, 101: 20359-20375.
5. Solymar, M. and I.L. Fabricius, 1998. Image analysis and estimation of porosity and permeability of arnager greensand, upper cretaceous. Denmark. J. Phys. Chem. Earth, 24: 587-591.
6. Atkinson, G.D., S. Bloch and M.H. Scheihing, 1990. Sedimentology and depositional environments of the Oligo-Miocene gas-bearing succession in the Yacheng 131 field, South ChinaSea, Peoples Republic of China AAPG Bulletin, 74: 601.
7. Schwartz., L. and J. Banavar, 1989. Transport properties of disordered continuum systems Physical Review B., 39: 11965-11970.
8. Rezaee, M.R. and N. Lemon, 1997. Permeability Estimation from Mercury Injection Capillary Pressure Data, cases study in the Tirrawarra Sandstone, Cooper Basin. Australian Petroleum Production and Exploration Association Journal, 37: 824.
9. Ahmed, U., S. Crary and G. Coates, 1991. Permeability estimation: the various sources and their interrelationship Journal of Petroleum Technology, 43: 578-587.
10. Vernik, L. and A. Nur, 1991. Lithology prediction and storage/transport properties evaluation in clastic sedimentary rocks using seismic velocities AAPG Bulletin, 75: 384.
11. Ehrlich, R., S.J. Crabtree, K.O. Horkowitz and J.P. Horkowitz, 1991. Petrography and reservoir physics I: Objective classification of reservoir porosity AAPG Bulletin, 75: 1579-1592.
12. Maqsood, A. and C. Adwait, 1999. Using artificial intelligence to predict permeability from petrographic data. Journal of Computers and Geoscience, 26: 915-925.
13. Anselmetti, F.S., S. Luthi and G.P. Eberli, 1998. Quantitative characterization of carbonate pore systems by digital image analysis. AAPG Bulletin, 82: 1815-1836.
14. Jamialahmadi, M. and F.G. Javadpour, 1999. Relationship of permeability, porosity and depth using an artificial neural network. Journal of Petroleum Science and Engineering, 26: 235-239.
15. Mohaghegh, S., 2000. Virtual-Intelligence Applications in Petroleum Engineering: Part 1-Artificial Neural Networks, Journal of Petroleum Technology. September 2000.
16. Bhatt, A. and H.B. Helle, 2002. Committee neural networks for porosity and permeability prediction from well logs. Geophys. Prospect, 50: 645-660.
17. Lim, J., 2005. Reservoir properties determination using fuzzy logic and neural network from well log data in offshore Korea. Journal of Petroleum Science and Engineering, 49: 182-192.
18. Kadkhodai, A., M.R. Rezaee and S.A. Moallemi, 2005. A New Approach for Prediction of Porosity, Permeability and Rock Types Using Soft Computing Techniques, An Example from Southern Persian Gulf, Petroleum Geoscience Collaboration Conference, London 30 November.

19. Kadkhodaie, A., H. Rahimpour-Bonab and M.R. Rezaee, 2009. A committee machine with intelligent systems for estimation of total organic carbon content from petrophysical data: An example from Kangan and Dalan reservoirs in South Pars Gas Field, Iran, Journal of Computers & Geosciences. 35: 459-474.
20. Dorigo, M. and G. Di Caro, 1999. The Ant Colony Optimization meta-heuristic," in New Ideas in Optimization, D. Corne *et al*., Eds., McGraw Hill, London, UK, pp: 11-32.
21. Serra, O., 1984. Fundamentals of well logging: The Acquition of Logging Data. Elsevier Press, NewYork, pp: 435.
22. Bishop, C.M., 1998. Neural Networks for Pattern Recognition. Clarendon Press, Oxford, pp: 256.