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Keywords:	ant colony algorithm, ANN, Bottom Hole Circulating Pressure, Two Phase Fluid, Underbalanced Drilling, Back propagation

An Improved Ant Colony Algorithm-Based ANN for Bottom Hole Pressure Prediction in Underbalanced Drilling

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Abstract

Ant colony optimization algorithm (ACA) has the powerful ability of searching the global optimal solution, and backpropagation (BP) algorithm has the feature of rapid convergence on the local optima. The proper hybrid of the two algorithms (ACA-BP) may accelerate the evolving speed of neural networks and improve the forecasting precision of the neural networks. ACA-BP scheme adopts ACA to search the optimal combination of weights in the solution space, and then uses BP algorithm to obtain the accurate optimal solution quickly. The ACA-BP and BP algorithms were applied to predict bottom hole pressure in Underbalanced Drilling. Experiment results show that the proposed ACA-BP scheme is more efficient and effective than BP algorithm.

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1. Introduction

The proposed models for two phase flow fall into two categories; flow-pattern-independent models and flow-pattern-dependent models. The first category consists of early models like Wallis (1969), Lockhart and Martinelli (1949). In the following years, flow patterns were determined by the researchers and then the flow parameters were presented for each individual flow pattern. These models are called mechanistic models which are still in their developing phase. Ross (1995) developed a simulator to evaluate pressures in the vertical drill string and

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reported that the model calculations under-predict the measured pressures all the time (Ross, 1995).

Most of the application of Artificial Neural Networks in two phase flow is just confined to pipes. Mohammadi (2006) found an average absolute error of 15.31 in the prediction of liquid hold up (Mohammadi, 2006). Ozbayoglu (2002) found fairly good bed heights estimations by ANN (Ozbayoglu, 2002). Flow pattern and frictional pressure drop were predicted by Ozbayoglu (2007) using ANN. Neural Networks estimated flow pattern with less than 5% error and frictional pressure drop with less that 30% error (Ozbayoglu, 2007). In 2002, Silpngarmlers found satisfactory results for three phase relative permeability compared with experiments (Silpngarmlers, 2002). This study attempts to combine ACA (ant colony algorithm), avoiding local minima and achieving global convergence quickly and correctly by searching in several regions simultaneously.

The ant colony algorithm (ACA) (Colorni et al., 1992) is a new stochastic search method that appears in the field of combinatorial optimization. Having strong robustness, suiting distributed computing and using positive feedback mechanism are the main characteristics of ACA, and it has already been proved that ACA can be used to solve complex optimization problems (Dreo et al., 2002).

In this paper, a hybrid of ACA and BP (ACA-BP) algorithms is proposed to evolve NNs. The ACA-BP algorithm firstly uses ACA algorithm to search the near-optimal solution and then adopts BP algorithm to find the accurate solution. The former attempts to avoid being trapped in the local optima and the later can rapidly find the accurate solution to accelerate its evolving speed.

The outline of this paper is as follows. First, in Section 2, we introduce the multilayer feed-forward neural network model, the ant colony algorithm, and methodology to hybrid ant colony with a back-propagation algorithm for neural network training. A case study is introduced in section 3. Simulation results are provided in Section 4 to demonstrate the effectiveness and potential of the new proposed hybrid algorithm for bottom hole circulating pressure compared with BP neural network using the same observed data. Finally, several conclusions are included in Section 5.

2. Methodology

2.1. Neural networks

Artificial neural networks are a large class of parallel processing architectures, which can mimic complex and non-linear relationships through the application of many non-linear processing units called neurons. The relationship can be 'learned' by a neural network through adequate training from the experimental data (Lin et al., 2008) Artificial neural network provides a parameterized, non-linear mapping between inputs and outputs. It has the inherent capability to deal with fuzzy information, whose functional relations are not clear (Mandal et al., 2007). Neural networks are clearly extremely useful in recognizing patterns in complex data. The resulting quantitative models are transparent; they can be interrogated to reveal the patterns and the model parameters can be studied to illuminate the significance of particular variables (Bhadeshia, 1999).

A three layered feed-forward neural network with back propagation algorithm can map any non-linear relationship with a desired degree of accuracy.(Hornik et al., 1989) In this paper, a three layer back propagation network (Figure 1) is developed to predict bottom hole circulating pressure, where the transfer functions in hidden and output layer are sigmoid and linear, respectively. The seven parameters measured depth, true vertical depth, drill pipe injected gas and liquid flow rates, casing pressure, surface temperature and liquid density at surface in Eq. (1) are the inputs to the ANN; bottom hole circulating pressure in Eq. (1) is the output of the network. The number of hidden layer is fixed to 5 by trail. Then a network model with 7-5-1 architecture is established (Figure 1).

During the BP network learning process, the error is subsequently backward propagated through the network to adjust the weights of the connections and threshold, minimizing the sum of the mean squared error (MSE) in the output layer,

$$U = \frac{1}{2}\sum_{k=1}^{G}\sum_{j=1}^{m}\left[T_j(k) - Y_j(k)\right]^2, \tag{1}$$

Where U is the sum of the mean squared error, m is the number of output nodes, G is the number of training samples, $T_j(k)$ is the expected output, and $Y_j(k)$ is the actual output.

It should be noted that a potential difficulty with the use of powerful non-linear regression methods is the possibility of overfitting data. In the above developed model, to avoid this difficulty, the experimental data are divided into two sets, a training dataset and a validating dataset. The model is produced using only the training data. The validating data are then used to check that the model behaves well when presented with previously unseen data. In addition, the proper selection of the number of neurons in the hidden layer can avoid the overfitting of neural network effectively.

2.2 Ant Colony Algorithm (ACA)

ACA simulates the behavior of real ants (Dorigo et al., 1996). It is based on the principle that using simple communication mechanisms, an ant colony is able to find the shortest path between any two points. During their trips, a chemical trail (pheromone) is left on the ground. The pheromone guides other ants toward the target point. For one ant, the path is chosen according to the quantity of pheromone. The pheromone evaporates over time (i.e., it loses quantity if other ants lay down no more pheromone). If many ants choose a certain path and lay down pheromones, the quantity of the trail increases, and thus, this trail attracts more and more ants.

From the above analysis, we can know it shows a positive feedback process when the ant colony finds its path (Walter et al., 2000). Compared with the ant colony in nature, the artificial ant colony has certain memory ability. It can memorize the node that has been visited. Moreover, when the artificial ant colony chooses the next path to go, it is not completely aimless, but seeks the shortest path consciously according to a certain algorithm rule.

Let $S=\{S|1,2,...,n\}$ is the food source (node) set that the ant individual in the ant colony system should search; $A=\{a|1,2,...,m\}$ is the ant colony, where m is the amount of all ants in A; $d_{ij}(i.j\in S)$ is the Euclidean distance between node I and node j; $\tau_{ij}(t)$ is the residual information quantity on path ij at moment t. In the initial time, the information quantity is equal on each path, that is $\tau_{ij}(0)=c$, where c is a constant.

According to the ACA transition probability criterion, the taboo list $tabu_k \left(k = 1, 2, \ldots, m\right)$ is used to record nodes that ant k has passed through currently. During the process of optimizing, the transition probability of ant k transfers from node i to node j is $p_{ij}^k(t)$ defined as following (equation 2):

$$p_{ij}^k(t) = \begin{cases} \dfrac{[\tau_{ij}(t)]^\alpha [\eta_{ij}]^\beta}{\sum\limits_{k=allowedk} [\tau_{ij}(t)]^\alpha [\eta_{ij}]^\beta} & \text{if } j \in \text{allowed}_k \\ 0 & \text{Otherwise} \end{cases} \qquad (2)$$

in which $\text{allowed}_k = \left\{S - tabu_k\right\}$ means the node allowed to be selected by ant k next step; $\eta_{ij} = 1/d_{ij}$ is the heuristic information on road ij ; α is the relative importance of information quantity on road ij , β is the relative importance of heuristic information (James et al., 2002), these two parameters need to be manually adjusted based on experiment. In order to reduce the probability that the algorithm falls into local optimal solution in a certain degree, the revision algorithm proposed by Gambardella is carried on to modify the transition probability $p_{ij}^k(t)$ (Gambardella et al., 1996). Let ant k transfer from node i to node j in the probability just as equation 3:

$$j = \begin{cases} \arg\max\left\{[\tau_{ij}(t)]^\alpha [\eta_{ij}]^\beta\right\} & \text{if } q \le q_0 \\ \text{Choose j based on equation (2)} & \text{otherwise} \end{cases} \qquad (3)$$

Where $q \in \left(0,1\right)$ is a random number, $q_0 \left(0 \le q_0 \le 1\right)$ is the initial hypothesis parameter, the relationship between these two parameters indicates the path that ant k will go through, that is, if $q \le q_0$, an exploration of new route between node i and node j should be taken; otherwise, the decision of next transition probability will be made based on the information the path already had.

In order to avoid the problem of residual information submerge heuristic information caused by too much residual information, after each ant completes its visit to all n nodes, the information quantity on the path that the ant has passed through must be updated according to the equation 4:

$$\tau_{ij}(t+n)=\left(1-\rho\right)\tau_{ij}(t)+\rho\Delta\tau_{ij}(t) \tag{4}$$

$$\Delta\tau_{ij}(t)=\sum_{k=1}^{m}\Delta\tau_{ij}^{k}(t) \tag{5}$$

Where ρ is the volatilization coefficient, $\rho\in\left(0,1\right)$; $\Delta\tau_{ij}(t)$ is the increment of information quantity on path ij in this circulation; $\Delta\tau_{ij}^{k}(t)$ is the information quantity that ant k left on path ij in this circulation, it can be calculated by equation 6.

$$\Delta\tau_{ij}^{k}(t)=\begin{cases}Q\cdot Obj_k & \text{if ant k passed through path ij in this circulation}\\ 0 & \text{otherwise}\end{cases} \tag{6}$$

Where Q is a constant that affects the convergence rate of algorithm; Obj_k is the objective function value of ant k in this circulation, it can be calculated by equation 7. (The total means squared error of the ANN architecture).

2.3. Optimization with Ant Colony Algorithm

An ACA allows a population composed of many individuals to evolve under specified selection rules to a state that maximizes the fitness values (F) in Eq. (2). The objective of the optimization is to maximize the objective function Obj_k in Eq. (6) which would lead to the minimization of the total mean squared error (U) from Eq. (1). This makes the ideal prediction results of the ANN be obtained.

As seen in Eq. (1), the minimizing process of U value is the adjusting and optimizing process of weights and thresholds of the ANN. Therefore, the ACA is used to optimize the weights and thresholds of the ANN. It is the weights optimization that is addressed in the current work.

2.4. Weight connections optimization using hybrid ACA-BP

The ACA–BP is an optimization algorithm combining the ACA with the BP. Similar to the GA, the ACA algorithm is a global algorithm, which has a strong ability to find global optimistic result, this ACA algorithm, however, has a disadvantage that the search around global optimum is very slow. The BP algorithm, on the contrary, has a strong ability to find local optimistic result, but its ability to find the global optimistic result is weak. By combining the ACA with the BP, a new algorithm referred to as ACA–BP hybrid algorithm is formulated in this paper. The fundamental idea for this hybrid algorithm is that at the beginning stage of searching for the optimum, the ACA is employed to accelerate the training speed. When the fitness function value has not changed for some generations, or value changed is smaller than a predefined number, the searching process is switched to gradient descending searching according to this heuristic knowledge.

The ANN learning process consists of two stages: firstly employing ACA to search for optimal or approximate optimal connection weights and thresholds for the network, then using the back-propagation learning rule and training algorithm to adjust the final weights. The operations are as follows. We defined the fitness function of the ith training sample as follows:

$$\text{Fitness}\,(X_i)=\text{MSE}(X_i) \tag{7}$$

When the ACA algorithm is used in evolving weights of neural network, every ant represent a set of weights.

3. Case Study

Parsi and Karanj fields are situated 130 km south east of Ahwaz. Parsi and Aghajari are located in North and South of Karanj respectively. Aghajari field is located in Omidiyeh City located 90 kms South of Ahvaz with length of 56 kms and width of 6 kms. It is located 200 kms South East of Ahvaz. Asmari Formation constitutes the reservoir of these three fields. Parsi Field has been producing for 45 years to date. Most of the underbalanced drilled wells of Iran have been drilled in these two fields. Gachsaran Oil Field is located 200 kms South East of Ahvaz. Gachsaran oil field with dimensions of 70 km long and 6-15 wide is one of the biggest carbonate reservoirs of Iran and contains fractured formations of Asmari, Bangestan and Khami. Other large oil fields from which measured data have been gathered are Marun and Aghajari. Marun is located approximately 50 kms southeast of Ahwaz in southwestern Iran. This elliptical field is approximately 65 kms long and 8 kms wide. Its nearest field, Aghajari, is less than two kms from southeastern edge of Marun. Lab-e-Sefid field is in the North of Marun field. Rag-e-Seid oil field is one of the big reservoirs at southwest of Iran situated in south Dezful City with 55 km length and 3-7 km width. It contains oil and gas reserved in Asmari, Bangestan and Khami formations. The map of these fields is shown in Figure 2.

Although a number of intelligent solution approaches have been done for two phase flow through pipes, few researches have been focused on two phase fluid systems in annular geometries. Because of the complexity of the two phase flow problems and immaturity of the mechanistic models, mechanistic modelling cannot satisfy the accuracy demand. Thus it is intended to determine the flow parameters of aerated drilling fluids flowing through inclined annuli using ANN and ant colony. The model incorporates fluid properties and pipe sizes.

Therefore in this study, hybrid ant colony algorithm-back propagation neural network would be applied to estimate Bottom Hole Circulating Pressure (BHCP) by using the experimental data coming from all the available data from the pressure and other sensors in Parsi, Karanj, Gachsaran, Maroon, Aghajari, Lab-e-sefid, Rag-Sefid oil fields.

Our goal was to develop a robust model that could predict the BHCP with only experimental data. Variables used for this development were measured depth, true vertical depth, drill pipe injected gas and liquid flow rates, casing pressure, surface temperature and liquid density at surface. All the input data have been normalized.

In this study, the best ANN architecture was: 7–5–1 (7 input units, 5 hidden neurons, 1 output neuron). The developed ANN model trained with back propagation (BP) has 5 hidden neurons in the mid-layer and sigmoid and linear activation functions in hidden and output neurons, respectively. Before training and testing, all source data are normalized into the range between -1 and 1 by using the maximum and minimum values of the variable over the whole data sets.

Figures 3 and 4 show the result of BHCP prediction compared with the actual measurements for both ACA-BP and BP-ANN. Note that the validation data were not used during the training process (about 25 percent of all the data sets were used as the validation data set).

4. Results and discussion

In order to evaluate the performance of the hybrid ACA-BP algorithm, a back-propagation neural network (BP-ANN) was applied with the same data sets used in the ACA–BP model. For each case, 10 runs, each starting from a different randomly generated population, have been performed. Figures 3 and 4 show the comparison between predicted and measured normalized BHCP values at validation phases for both hybrid ACA–BP and BP-ANN models. The ACA–BP algorithm was run with a population size of 10. ACA–BP was trained by 100 generations, followed by a BP training procedure. The value of learning coefficient 0.7 and momentum correction factor 0.001 were used for the back-propagation training algorithm.

In Figure 3 the output of the model, simulated with validation data, shows a good agreement with the target. The simulation performance of the ACA–BP model was evaluated on the basis of mean square error (MSE) and efficiency coefficient R^2 (Nash & Sutcliffe, 1970). The parameters MSE = 2.1e-4 and R^2 = 0.992 in contrast to MSE= 2.2e-3 and R^2 = 0.852 for BP-ANN, suggest a very good performance of ACA-BP. In general, a R^2 value greater than 0.9 indicates a very satisfactory model performance, while a R^2 value in the range 0.8–0.9 signifies a good performance and value less than 0.8 indicate an unsatisfactory model performance (Coulibaly & Baldwin, 2005).

Figures 5 and 6 show the extent of the match between the measured and predicted permeability values by ACA–BP and BP-ANN networks in terms of scatter diagrams. These results show that ACA-BP has the capability of avoiding being trapped in local optimums and this is due to the combination of global searching ability of ACA and local searching ability of BP.

Table 1 gives the MSE and R^2 values for the two different models of the validation phases. It can be observed that the performance of ACA–BP is better than that by the BP-ANN models.

5. Conclusion and future work

In this article, we have presented an ant colony evolved neural network. Our methodology presents a hybrid ant colony algorithm- back propagation neural network (ACA-BP), which effectively combines the local searching ability of the back propagation method and the global searching ability of ant colony algorithm. The idea of our algorithm is that each initial point of the back propagation neural network is selected by a standard ant colony algorithm and the fitness of the ant colony algorithm is determined by a neural network. The ant colony parameters are carefully set to optimize the neural network, avoiding premature convergence and permutation problems. The experiment with real well logs and core measurements data has showed that the predictive performance of the proposed model is better than that of the traditional BP neural network (BP-ANN). This has been supported by the analysis of the changes of connection weights and biases of the neural network.

One problem when considering the combination of neural network and ant colony algorithm for permeability estimation is the determination of the optimal neural network topology. Our neural network topology described in this experiment is determined manually. A substitute method is to apply the genetic algorithm for neural network structure optimization, which will be a part of our future work.

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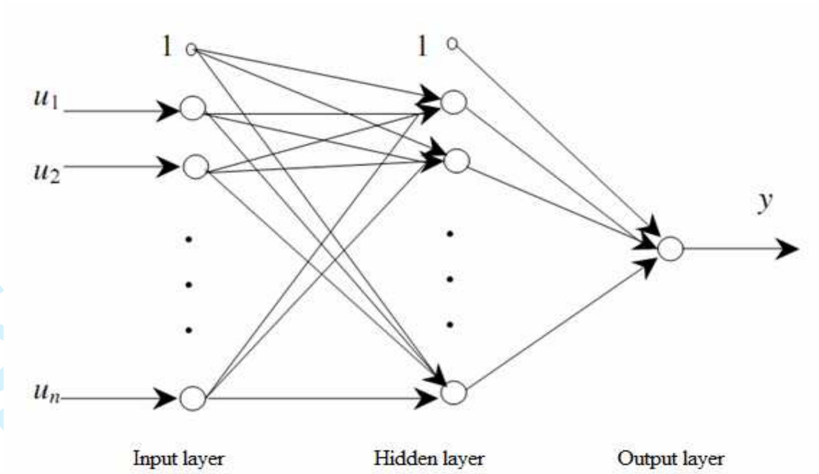

Fig.1. A Feed-forward Artificial Neural Network Structure

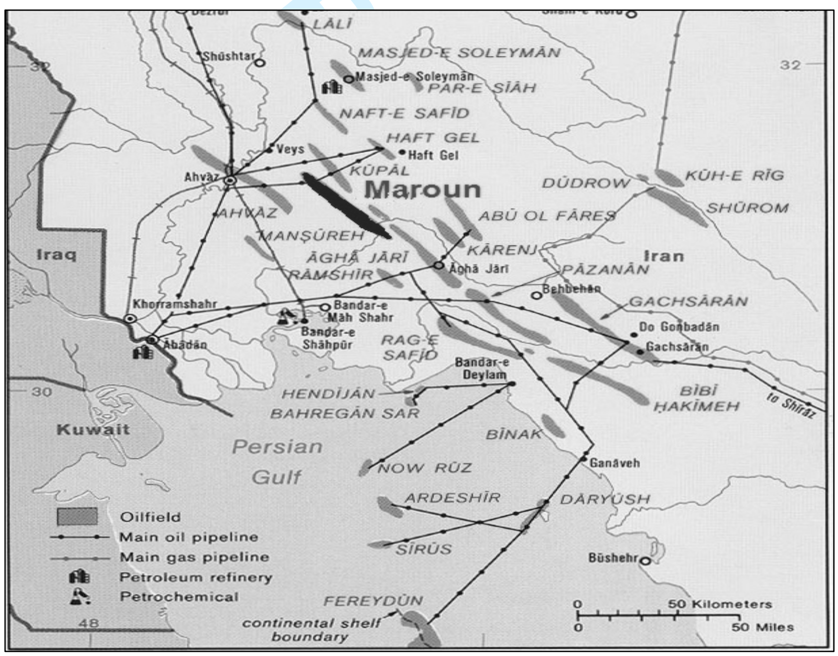

Fig.2. Map of South Iranian oil fields

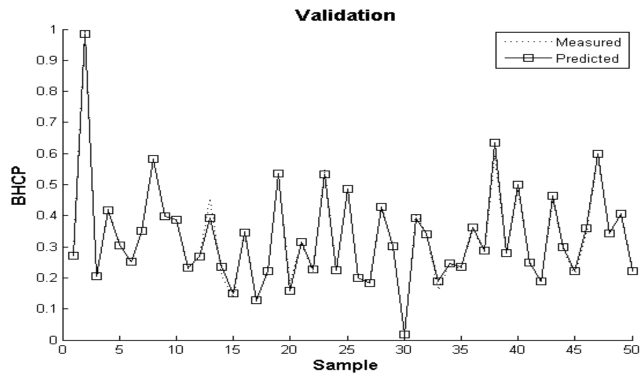

Fig.3. Comparison between measured and predicted normalized BHCP (ACA-BP) - Validation phase

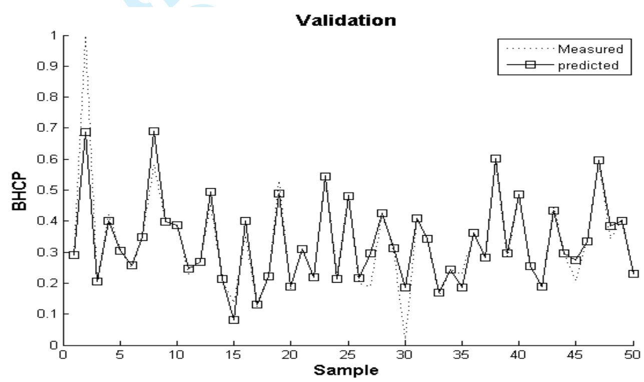

Fig.4. Comparison between measured and predicted normalized BHCP (BP-ANN) - Validation phase

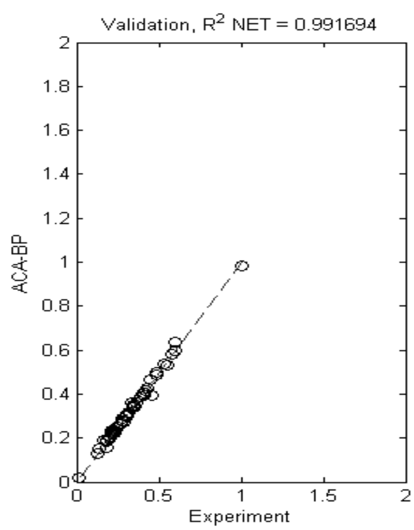

Fig.5. R^2 (ACA-BP)

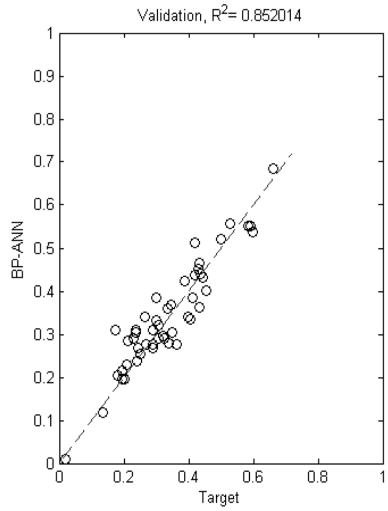

Fig.6. R^2 (BP-ANN)

Table1. Comparison between the performances of ACA–BP and BP-ANN neural networks

	ACA-BP	BP-ANN
MSE	2.1e-4	2.2e-3
R^2	0.9916	0.852