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Evolving neural network using real coded genetic algorithm for permeability estimation of the reservoir

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ABSTRACT

In this work we investigate how artificial neural network (ANN) evolution with genetic algorithm (GA) improves the reliability and predictability of artificial neural network. This strategy is applied to predict permeability of Mansuri Bangestan reservoir located in Ahwaz, Iran utilizing available geophysical well log data. Our methodology utilizes a hybrid genetic algorithm–neural network strategy (GA–ANN). The proposed algorithm combines the local searching ability of the gradient–based back-propagation (BP) strategy with the global searching ability of genetic algorithms. Genetic algorithms are used to decide the initial weights of the gradient decent methods so that all the initial weights can be searched intelligently. The genetic operators and parameters are carefully designed and set avoiding premature convergence and permutation problems. For an evaluation purpose, the performance and generalization capabilities of GA–ANN are compared with those of models developed with the common technique of BP. The results demonstrate that carefully designed genetic algorithm-based neural network outperforms the gradient descent-based neural network.

1. Introduction

The key parameter for reservoir characterization is the permeability distribution. In most reservoirs permeability measurements are rare and therefore permeability must be predicted from the available data. Generally, geophysical well logs are the most abundant source of data. Predicting permeability from well log data in heterogeneous reservoirs is a complex problem.

Neural networks have been increasingly applied to predict reservoir properties using well log data (Mohaghegh, Arefi, Ameri, & Rose, 1994; Mohaghegh, Balan, & Ameri, 1995; Wiener, 1995). Moreover previous investigations (Aminian, Bilgesu, Ameri, & Gil, 2000; Aminian, Thomas, Bilgesu, Ameri, & Oyerokun, 2001; Wong, Jang, Cho, & Gedeon, 2000) have indicated that artificial neural networks (ANNs) can predict formation permeability even in highly heterogeneous reservoirs using geophysical well log data with good accuracy.

Conventional gradient-based techniques are prone to getting into local optimum and convergence is slow. To overcome these drawbacks, this study attempts to combine GA (genetic algorithm), avoiding local minima and achieving global convergence quickly and correctly by searching in several regions simultaneously.

There are two main aspects to apply GA into ANN (Whitfield & Martin, 1986), as follows: one is to optimize the weights of the network, and the other is to optimize the topological structure of the network. The former will be discussed in this paper. The learning process of network is considered as the dynamic process for continuous optimization of the weights and thresholds. GA is an optimization and search technique based on the principles of genetics and natural selection. GA has remarkable abilities which include being able to solve non- smooth, non-continuous, non-differentiable fitness functions, to escape the local optima and acquire a global optimal solution.

GAs are found to be quite useful and efficient when the exploration space of the ANN is extensive. The researches by Van Rooij, Jain, and Johnson (1996) and Vonk, Jain, and Johnson (1997) have proposed using evolutionary computations, such as GAs in the field of ANNs to generate both the ANN architecture and its weights. Those (Bornholdt & Graudenz, 1992; Marshall &, 1991; Miller, Todd, & Hedge, 1989) who supported the proposal were in favour of optimizing the connection weights and the architecture of ANNs using GAs. In addition, the researches on permeability estimation from well logs by Chena and Lina (2006), Huanga, Gedeonb, and Wongc (2001) showed that it is highly effective to apply integrated GAs to ANNs in permeability prediction. However, these works did not cover the optimization of ANN parameters using GAs. Saemi, Ahmadi, and Yazdian (2007) developed a methodology for designing of the neural network architecture using genetic algorithm and showed that the neural network model incorporating a GA was able to sufficiently estimate the permeability reservoir with high correlation coefficient. Sedki, Ouazar, and El Mazoudi (2009) used an Evolving neural network using genetic algorithm to predict daily rainfall–runoff. An efficient evolving neural network using

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particle swarm optimization was applied by Nasimi, Shahbazian, and Irani (2010) for permeability estimation of the reservoir.

The outline of this paper is as follows. First, in Section 2, we introduce the multilayer feed-forward neural network model, the genetic algorithm, and methodology to hybrid real coded GA with a back-propagation algorithm for neural network training. Simulation results are provided in Section 3 to demonstrate the effectiveness and potential of the new proposed hybrid algorithm for permeability prediction in Mansuri Bangestan reservoir compared with BP neural network using the same observed data. Finally, several conclusions are included in Section 4.

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, Zhang, & Zhong, 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, Sivaprasad, & Dube, 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, Stinchcombe, & White, 1989) In this paper, a three layer back propagation network (Fig. 1) is developed to predict permeability, where the transfer functions in hidden and output layer are sigmoid and linear, respectively. The five parameters (DT, NPHI, RHOB, SGR, PHIT log) in Eq. (1) are the inputs to the ANN; permeability in Eq. (1) is the output of the network. The number of hidden layer is fixed to 7 by trail. Then a network model with 5-7-1 architecture is established (Fig. 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,

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

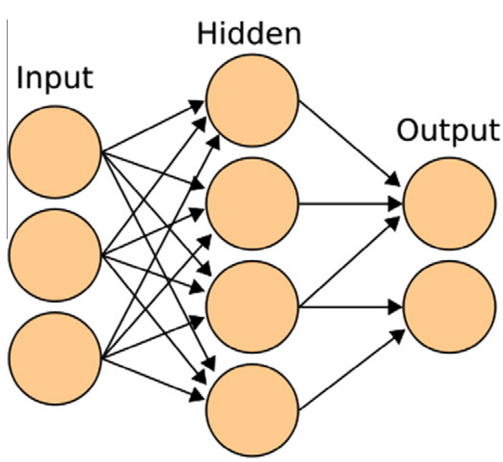

Fig. 1. Architecture of three-layer ANN.

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. Genetic algorithm

Fitness function and genetic operation of GA. GA has been proved to be capable of finding global optima in complex problems by exploring virtually all regions of the state space and exploiting promising areas through mutation, crossover and selection operations applied to individuals in the populations (Hardalac, 2009) It applies selection, crossover and mutation operators to construct fitter solutions. A genetic algorithm processes the populations of chromosomes by replacing unsuitable candidates according to the fitness function. In this study, the fitness function is the average deviation between expected and predicted values of permeability. The fitness value of a chromosome is calculated using the total mean squared error of the ANN architecture. A fitness value F is given by

$$F = \frac{1}{U} \tag{2}$$

where U is the sum of the mean squared error given by Eq. (1). Thus, the smaller the network's total mean squared error, the closer a fitness value to 1 (maximum). Once fitness values of all chromosomes are evaluated, a population of chromosomes is updated using three genetic operators: selection, crossover and mutation. The three operators are described as follows:

The selection operator of genetic algorithm is implemented by using the roulette-wheel algorithm to determine which population members are chosen as parents that will create offspring for the next generation. Crossover is a mechanism of randomly exchanging information between two chromosomes. The paper uses arithmetical crossover which can ensure the offspring are still in the constraint region and moreover the system is more stable and the variance of the best solution is smaller. Mutation operation can change the values of randomly chosen gene bits, and this process continues until some predefined termination criteria are fulfilled. Mutation operation aims to make genetic algorithm obtain local random research capability through varying certain genes of chromosome.

2.3. Optimization with genetic algorithm

A GA 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 fitness values (F) 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 GA is used to optimize the weights and thresholds of the ANN. It is the weights optimization that is addressed in the current work.

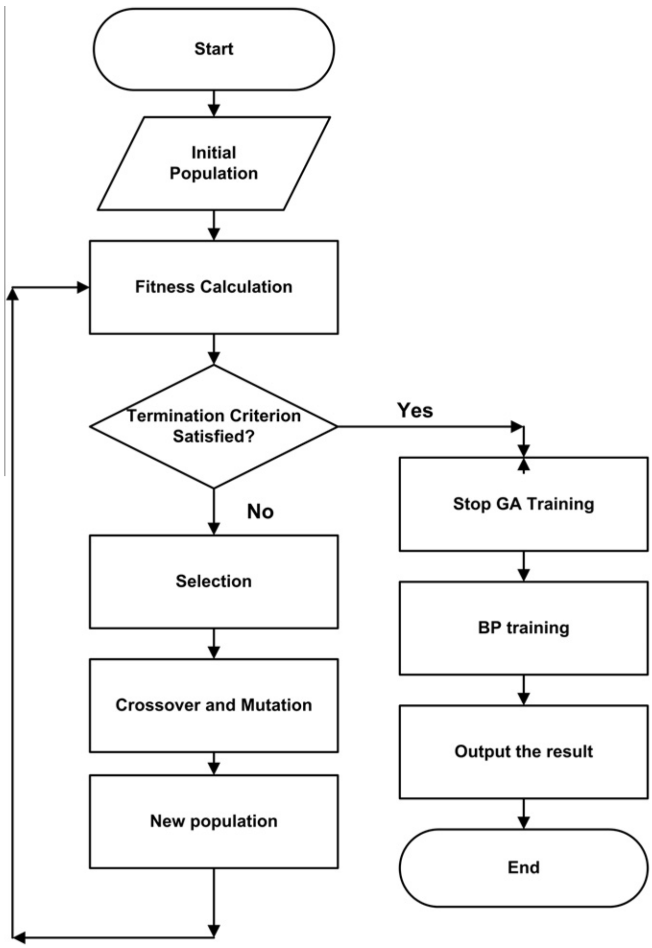

Fig. 2. Framework of combining neural network and GA.

2.4. Weight connections optimization using hybrid GA-ANN

The ANN learning process consists of two stages: firstly employing GA 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 (Fig. 2). The operations are as follows:

The ANN weights and thresholds are initialized as genes of chromosome, and then the global optimum is searched through selection, crossover and mutation operators of genetic algorithm. This procedure is completed by applying a BP algorithm on the GA established initial connection weights and thresholds.

3. Case Study

Mansuri field is located 40 km away from south of Ahvaz city. Geographically, this field neighbours with Ahvaz field to the north, Abteymur to the west and Shadegan to north east. This field dimension at WOC is 30 km in length and 3.5 km in width.

Mansuri field has two reservoirs: Asmari and Bangestan. Bangestan is the deeper reservoir and consists of three formations. These formations are: Ilam, Sarvak, and Kazhdomi. More than 46 wells have been drilled in Bangestan reservoir and almost all the wells have logging data. Only six wells in this reservoir have core data: wells 1, 4, 14, 25, 44 and 54. In this project, we only used the core data and logging data in wells that core analysis data were available for.

Our goal was to develop a robust model that could predict the permeability with only well log data for wells. Variables used for this development were gamma ray, bulk density, neutron porosity, sonic transit time, total porosity. In this study, the best ANN architecture was: 5-7-1 (5 input units, 7 hidden neurons, 1 output neuron). The developed ANN model trained with back propagation (BP) has 7 hidden neurons in the midlayer 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.

Figs. 3, 4 show the result of permeability prediction compared with the actual measurements for both GA–ANN and ANN. Note that the well logs and core measurements from 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 genetic algorithm-based neural network, back-propagation neural network was applied with the same data sets used in the GA–ANN model. Figs. 3, 4 show the comparison between predicted and measured permeability values at training and validation phases for both hybrid GA–ANN and ANN models using the well logs and core measurements from the Mansuri Bangestan reservoir. The GA–ANN algorithm was run with a population size of 100, uniform crossover probability was set to 0.9 and uniform mutation probability was set to 0.01. GA–ANN 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 Fig. 3 the output of the model, simulated with validation data, shows a good agreement with the target. The simulation performance of the GA–ANN model was evaluated on the basis of mean square error (MSE) and efficiency coefficient R^2(Nash & Sutcliffe, 1970). The parameters MSE = 1.4e$-$4 and $R^2 = 0.997$ in contrast to MSE = 0.0014 and $R^2 = 0.935$ for ANN, suggest a very good performance of GA–ANN (Figs. 5 and 6). 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).

Figs. 5 and 6 show the extent of the match between the measured and predicted permeability values by GA–ANN and ANN networks in term of a scatter diagram. These results show that GA–ANN has the capability of avoiding being trapped in local optimums and this is due to the combination of global search ability of GA with local search 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 GA–ANN is better than those by the ANN models.

5. Conclusion and future work

In this article, we have presented a genetic algorithm evolved neural network. Our methodology presents a genetic algorithm based neural network (GA_ANN), which effectively combines the local searching ability of the gradient decent method with the global searching ability of genetic algorithm. The idea of our algorithm is that each initial point of the neural network is selected by a standard genetic algorithm and the fitness of the genetic algorithm is determined by a neural network. The genetic operators are carefully designed 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

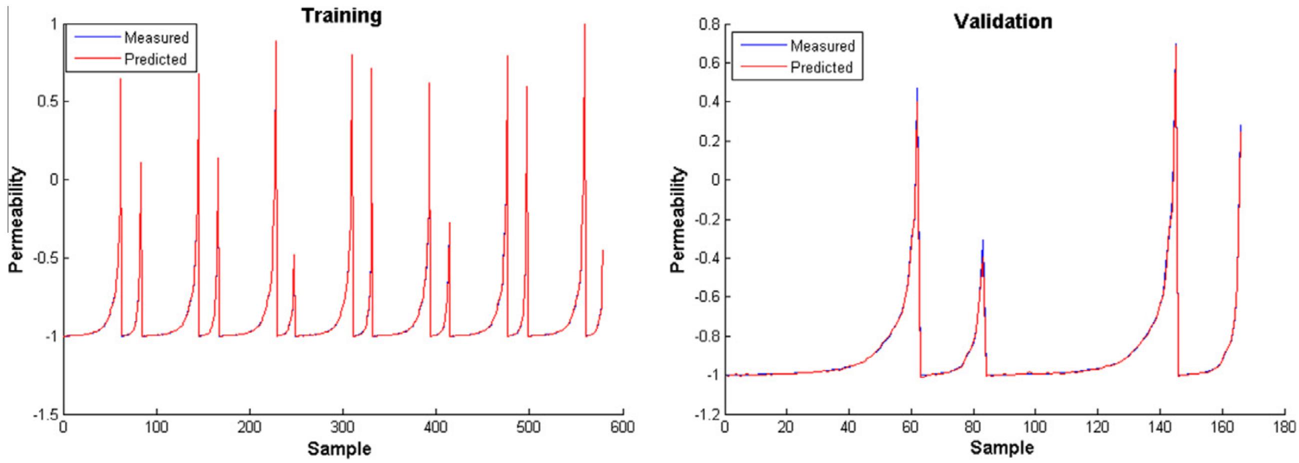

Fig. 3. Comparison between measured and predicted permeability (GA-ANN).

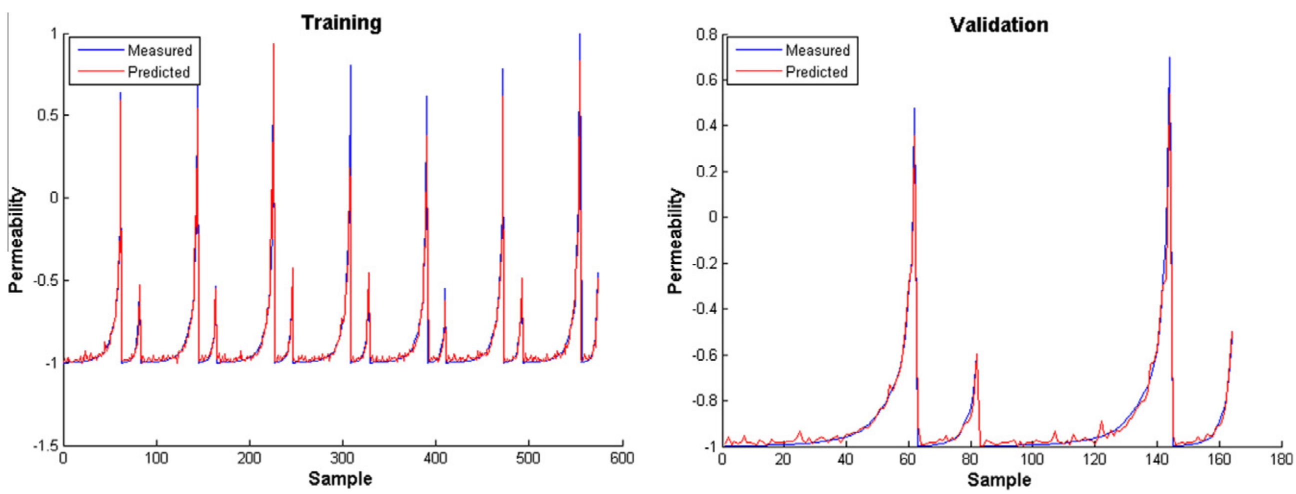

Fig. 4. Comparison between measured and predicted permeability (ANN).

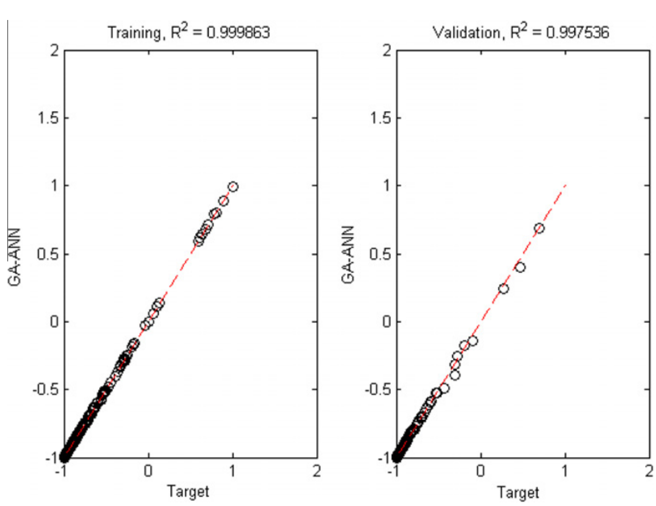

Fig. 5. R^2 (GA-ANN).

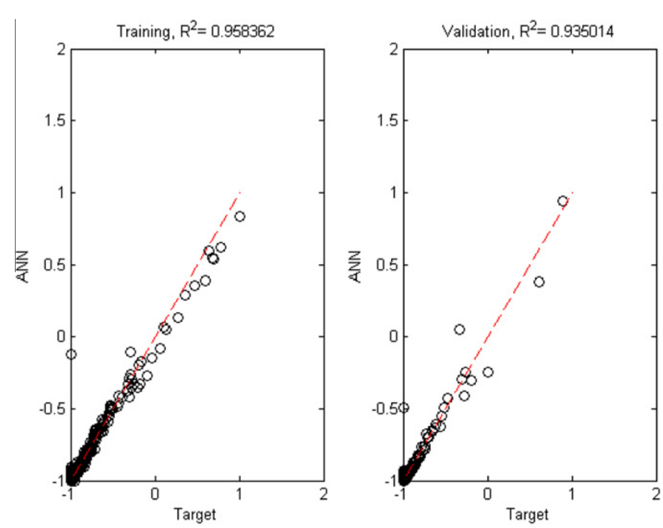

Fig. 6. R^2 (ANN).

traditional BP neural network. 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 genetic algorithm for permeability estimation is the determination of the optimal neural network topology. Our neural

Table 1
Comparison between the performances of GA-ANN and ANN neural networks.

	GA–ANN	ANN
MSE	1.4e−4	0.0014
R^2	0.997	0.935

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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