Estimation of Gas and Petroleum Reservoir Parameters Using an Integrated Approach Neural Network and Genetic Algorithm

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A new predictive methodology is introduced, based on a combined genetic algorithm (GA) and artificial neural network (ANN) methodologies for parameters estimation of a petroleum reservoir. Prediction of continuous petro-physical parameters is often time consuming and complicated because of geological variability such as facies changes due to sedimentary and structural changes. The petro-physical parameters, however, are usually difficult to measure due to reliability considerations, limitations insights on cost , inappropriate instrument maintenance and sensor failures, evaluated by crude diagrams of reservoir parameters valuably. 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. The developed soft sensors are applied to predict the parameters of Marun reservoir located in Ahwaz, Iran, by utilizing the available geophysical well log data. The resulting outcomes demonstrate the promising capabilities of the proposed hybrid GA-NN methodology than the conventional back propagation (BP) NN algorithms.

Keywords: Genetic Algorithm, Neural network, Well log data, Reservoir, Back propagation

1. INTRODUCTION

The accuracy of parameters estimation from the well log data is a crucial issue in the petroleum reservoirs. Over half a century, Electrical well logging is used to estimate of reservoirs properties. Crude logging diagrams are one of the important tools for evaluation of petro physical parameters and construction of three-dimensional models of hydrocarbon reservoirs. In the last few years, artificial intelligence has been involved in solving many problems in different fields of science. Many authors have dealt with the application of neural networks in solving fundamental problems in geophysical and petroleum engineering like Fu (1994), Haykin (1994), Mohaghegh et al.(1994, 1995) and Wiener (1995). Previous investigations (Wong et al, 2000) have indicated that artificial neural network can predict formation permeability even in highly heterogeneous reservoirs using geophysical well log data with good accuracy. The characterization and prediction of reservoir properties is an important application of ANNs in the oil industry. The input data to the prediction problem are usually processed and interpreted log data and/or a set of attributes derived from the original data set. Historically, many hydrocarbon indicators have been proposed to make such predictions. 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 et al., 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 et al. (1996) and Vonk et al. (1997) have proposed using evolutionary computations, such as GAs in the field of ANNs to generate both the ANN architecture and its weights. Those (Miller et al., 1989; Marshall and Harrison, 1991; Bornholdt and Graudenz, 1992) 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 Huanga et al. (2001), and Chena and Lina (2006) 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 et al. (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.

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 is presented in Section 3. Finally, the developed approach will be tested on a capture data from a well of Marun field.

2. NEURAL NETWORK

Neural networks can address some important problems which conventional computing has been unable to solve. The idea of artificial neural networks is to input a number of parameters related to each other by certain features and try to use these features to predict another one or two output properties. To develop a neural network model, two groups of data are very important. The first is the training group, which contains all the input parameters, while the other is the application group, which will be used in the final prediction. It provides non-linear mapping between inputs and outputs. For this purpose, each input is multiplied by a weight, the inputs are summed and this quantity is operated on by the transfer function of the neuron to generate the output. Also, it has the inherent capability to deal with fuzzy information, whose functional relations are not clear (Mandal et al., 2007). Here, the viability of Artificial Neural Network (ANN) algorithms will be demonstrated in estimating oil field reservoir parameters. There are a number of algorithms available for the above purpose but the most widely used is the back propagation (BP) algorithm (Masters, 1990). Training a network by gradient descent, feeding the errors backwards through the network, is called back propagation. For illustration purposes, consider a ANN with one hidden layer Fig 1. In BP algorithm, the error is subsequently backward propagated through the network to adjust the weights of the connections and threshold, minimizing the following sum of the mean squared error (MSE) in the output layer,

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

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.

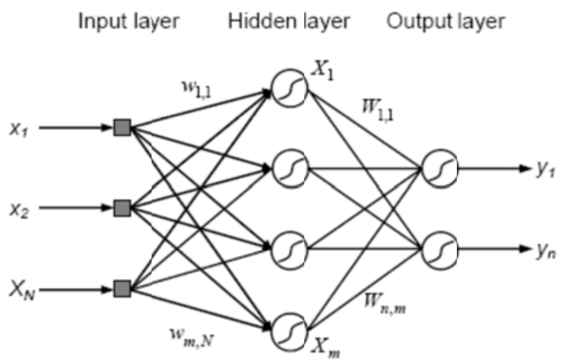

Fig. 1. A multi-layer neural network with one hidden layer of neurons.

3. GENETIC ALGORITHM AND HYBRID MODEL

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

$$F = \frac{1}{U} \qquad (2)$$

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.

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.

3.1. 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. 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.

4. CASE STUDY

Maroon field, representing an asymmetric anticline and located at the southeast of Ahvaz, Iran, is taken as a real case study. Production from this field is done on Asmari and Bangestan reservoirs, and the study is focused on the Asmari formation. Fig 2 shows the position of Marun field in Dezful Embayment. Asmari reservoir in the Maroon field containing almost 70% lime and dolomite and 30% sediment. The proposed approach is developed to construct a robust model that could predict the reservoir parameters with only well log data for wells. Eight different parameters of a reservoir are considered as the original parameters. These parameters, capturing from logging tools, are consisted of, depth in a well (DEPTH), that is the measurement for any point in the well, condensate-to-natural gas ratio (CGR) , sonic log(DT), neutron log(NPHI), photoelectric effect (PEF), resistivity log, density log(RHOB) and spectral gamma-ray (SGR). In this paper, the best ANN architecture with 10 hidden neurons has been chosen (7 input units, 5 hidden neurons, 1 output neuron). The developed hybrid GA-NN model trained with 5 hidden neurons in the hidden and sigmoid and linear activation functions in hidden and output neurons, respectively. Rock porosity can be obtained from sonic log, density log, or neutron log.

Fig. 2. Marun field position

5. RESULTS AND DISCUSSION

In order to evaluate the performance of the hybrid GA-NN algorithm, mean square errors (MSE) are considered as a common statistical measure. The comparative performances of the hybrid approach are evaluated respect to back propagation neural network (NN) and genetic algorithm-neural network (GA-NN) algorithms on a similar set of well log captured from a well, called as A, on the Asmari formation. The structure of the utilized NN has been configured with 7 input neurons, 5 hidden neurons and one output neuron. This enables the primary objective of predicting one of the eight reservoir parameters from the other remaining parameters. In each method neural network is trained 3 times and the values of MSE are computed in each time for reliability consideration, so their averages are considered for comparing. In this paper, two parameters are considered for predicting by the other parameters. Indeed, for more evaluating of the proposed algorithm, its ability to prediction is measured based on estimation of these two parameters. In the first stage, the first parameter is considered for predicting by the other parameters. The corresponding results of algorithms have been summarized in Table 1. Fig. 3, illustrates the comparative results corresponding to estimation of DEPTH by NN algorithm and estimation of data by the proposed hybrid GA-NN algorithm. As shown, GA-NN is able to estimate the DEPTH parameter by with a better performance compared to the NN algorithm.

Table 1.
Obtained results of prediction of DEPTH in terms of MSE measures

	NN (Training)	NN (Validation)	GA-NN (Training)	GA-NN (Validation)
MSE	5.5235e-005	8.3083e-005	3.0109e-005	4.8180e-005

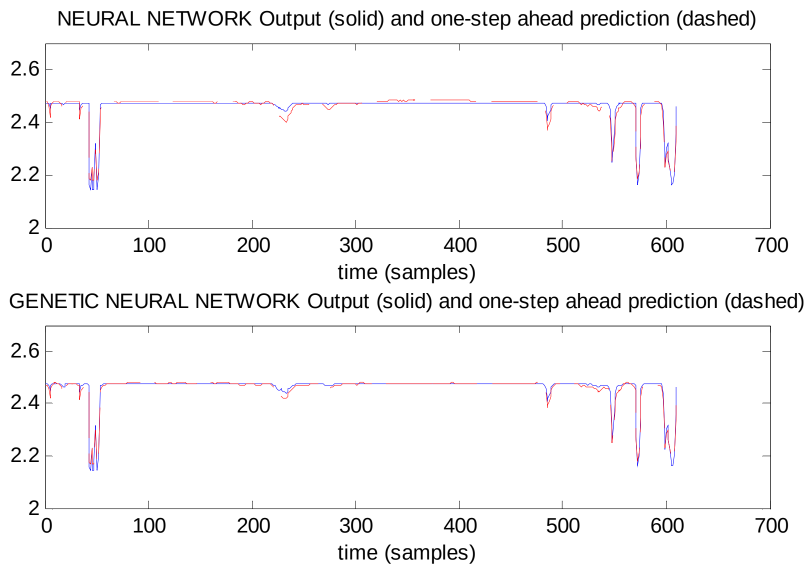

Fig. 3. Reservoir DEPTH estimation by NN and GA-NN

The simulation performance of the GA–NN model was evaluated on the basis of efficiency coefficient (Nash & Sutcliffe, 1970). The corresponding statistical efficiency coefficients (R) have been summarized from the algorithms in Table 2. Roughly speaking, R value greater than 0.9 indicates a very satisfactory model performance, while R value in the range 0.8– 0.9 signifies a good performance and value less than 0.8 indicate an unsatisfactory model performance (Coulibaly et.al, 2005).

Table 2.
The efficiency coefficients (R) of the two implemented algorithms for estimation of DEPTH

Neural network algorithm	GA & Neural Network
0.98429	0.99177

The parameters of the MSE = 4.8180e-005 and R^2 = 0.99177 for GA-NN algorithm in contrast to MSE= 8.3083e-005 and R^2 = 0.98429 for ANN, suggest a very good performance of GA-NN algorithm to estimation of parameters. (Fig. 3-4).

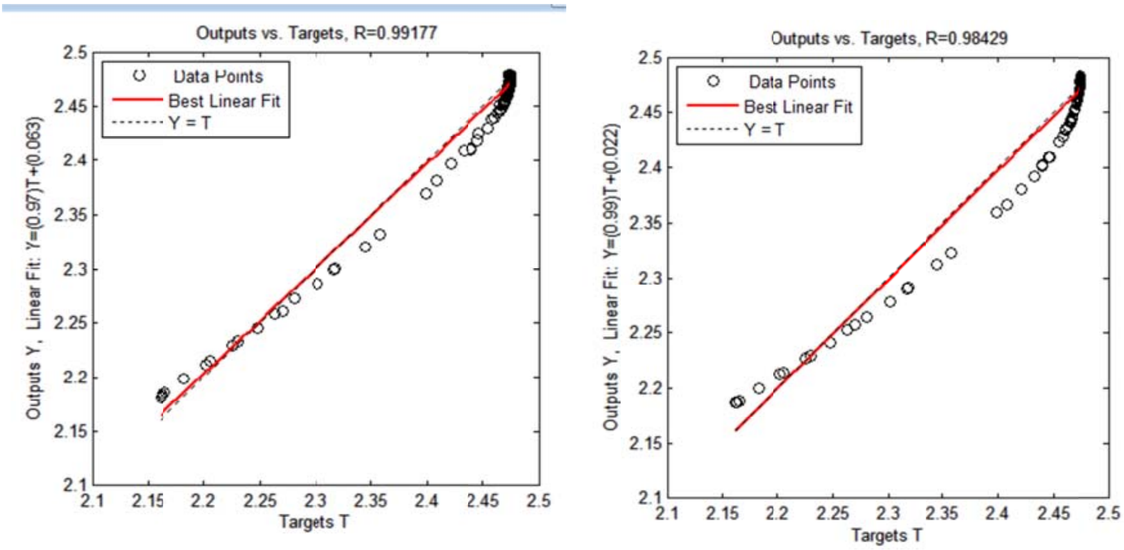

Fig.4. R^2 a) GA-ANN b) ANN

Fig. 3, 4 show the extent of the match between the measured and predicted 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. Now, the capability of the proposed algorithm is evaluated by estimating of the forth parameter neutron log (NPHI). The results are illustrated as follow:

Table 3.
Obtained results of prediction of NPHI in terms of MSE measures

	NN (Training)	NN (Validation)	GA-NN (Training)	GA-NN (Validation)
MSE	9.9702e-006	2.4827e-005	4.4113e-006	7.2513e-006

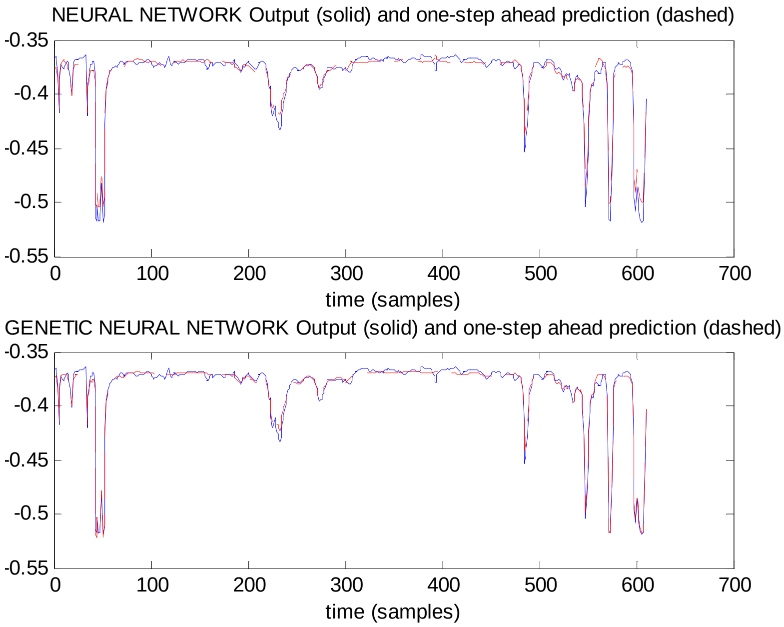

Fig. 5. Reservoir NPHI estimation by NN and GA-NN

Table 4.
The efficiency coefficients (R) of the two implemented algorithms for estimation of NPHI

Neural network algorithm	GA & Neural Network
0.99463	0.99641

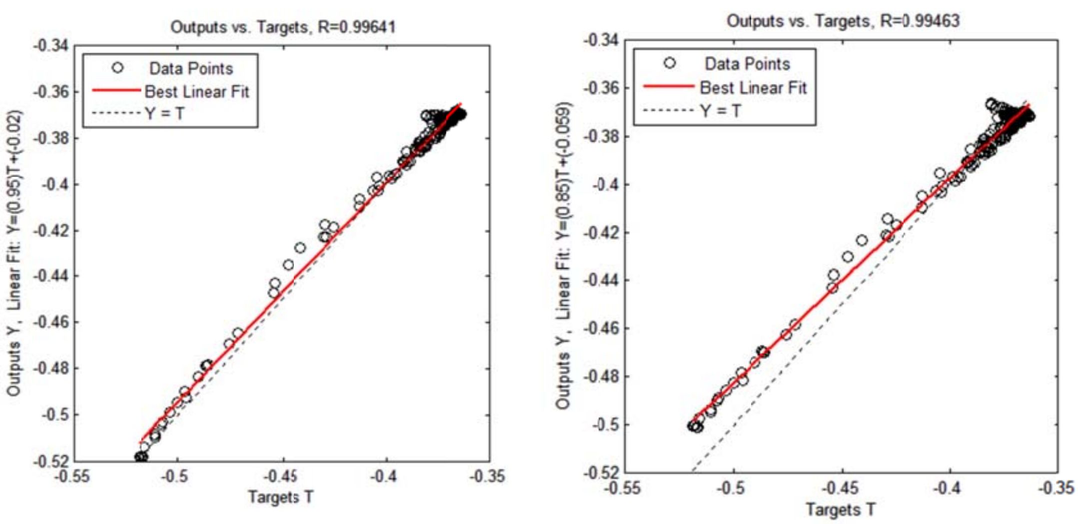

Fig.6. R^2 a) GA-ANN b) ANN

6. CONCLUSION

In this paper, a set of different soft sensors has been developed by incorporating genetic algorithm and neural network for estimation of petroleum reservoir parameters. The methodology utilizes a genetic algorithm for training of neural network which effectively increases the estimation accuracy. A set of simulation tests was carried out on a real data from reservoir to comparatively evaluate the resulting performances of the developed soft sensors. The simulation studies were performed on Marun field demonstrated promising results, implying that the proposed GA-NN algorithm could efficiently estimate the reservoir parameters better than the common back-propagation algorithms.

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