Permeability Prediction of Carbonate Reservoir by Combining Neural Network and Shuffled Frog-Leaping

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Abstract: Permeability is one of the most important rock parameters in reservoir engineering that affects fluids flow in reservoir. In most reservoirs, permeability measurements are rare and Permeability is determined from rock sample or well testing data. Core analysis and well test data are expensive and time consuming. In the present paper, the soft sensor based on a feed-forward artificial neural network (ANN) to estimate permeability of the reservoir is proposed. After that, ANN-based Soft-Sensor was optimized by Shuffled Frog-Leaping Algorithm (SFLA). SFLA is used to decide the initial weights of the neural network. The SFLA-ANN based soft sensor is applied to predict permeability in one of the northern Persian Gulf oil fields of Iran reservoir located in Ahwaz, Iran utilizing available geophysical well log data. The performance of the SFLA-ANN based soft sensor is compared with ANN based soft sensor. The results demonstrate the effectiveness of the SFLA-ANN based soft sensor.

[Mohammad Ali Ahmadi, Seyed Reza Shadizadeh. **Permeability Prediction of Carbonate Reservoir by Combining Neural Network and Shuffled Frog-Leaping.** Journal of American Science 2012;8(2):529-533]. (ISSN: 1545-1003). http://www.americanscience.org. 73

Keywords: Neural Network; Shuffled Frog-leaping Algorithm; Permeability; Well log data; Prediction

1. Introduction

Permeability is the key parameter of the reservoir. In most reservoirs, permeability measurements are rare and therefore permeability must be measured in the laboratory from reservoir core samples or evaluated from well test data. However, core analysis and well test data are usually only available from a few wells in a field. Unfortunately, coring every well in large fields is very expensive and uneconomical.

A soft sensor is a conceptual device whose output or inferred variable can be modeled in terms of other parameters that are relevant to the same process (Rallo et al., 2002).According to Rallo et al. (2002), artificial neural network could be used as soft sensor building approach. The ANN is a popular, nonlinear, nonparametric tool in well log analysis. This technique has been increasingly applied to predict reservoir properties using well log data (Doveton and Prensky, 1992;Balan et al., 1995).

The determination of network structure and parameters are very important; some evolutionary algorithms such as Genetic Algorithm (GA) (Qul et al., 2008), Back Propagation (BP) (Tang and Xi,2008), Pruning Algorithm (Reed, 1993), Simulated Annealing (Souto et al., 2002) can be used for this determination. At the same time, since NN training can be consider as a type of optimization problem. Recently some evolutionary algorithms inspired by social behavior in the nature are also developed to solve NN training, such as particle swarm paradigm, which simulates swarm behavior of ants or birds. Although Particle Swarm Optimization (PSO) was just developed in 1995 (Eberhart and Kennedy, 1995), it has become as hot topic involving optimization issues (Juang, 2004; Van den Bergh and Engelbrecht, 2001).

In the present work, we propose SFLA for optimizing the weights of feed-forward neural network. Then Simulation results demonstrate the effectiveness and potential of the new proposed network for permeability prediction in one of the northern Persian Gulf oil fields of Iran reservoir compared with BP neural network using the same observed data.

2. Artificial neural networks

Artificial neural networks are parallel information processing methods which can express complex and nonlinear relationship use number of input-output training patterns from the experimental data. ANNs provides a non-linear mapping between inputs and outputs by its intrinsic ability (Hornik and Stinchcombe, 1990) .The success in obtaining a reliable and robust network depends on the correct data preprocessing, correct architecture selection and correct network training choice strongly (Garcia et al., 2003).

The most common neural network architecture is the feed-forward neural network. Feed-forward network is the network structure in which the information or signals will propagates only in one direction, from input to output. A three layered feed-forward neural network with back propagation algorithm can approximate any nonlinear continuous function to an arbitrary accuracy (Brown and Harris, 1994; Hornick and Stinchcombe, 1989).

The network is trained by performing optimization of weights for each node interconnection and bias terms; until the values output at the output layer neurons are as close as possible to the actual outputs. The mean squared error of the network (MSE) is defined as:

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

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

The data are split into two sets, a training data set and a validating data set. The model is produced using only the training data. The validating data are used to estimate the accuracy of the model performance. In training a network, the objective is to find an optimum set of weights. When the number of weights is higher than the number of available data, the error in fitting the non-trained data initially decreases, but then increases as the network becomes over-trained. In contrast, when the number of weights is smaller than the number of data, the over fitting problem is not crucial.

3. Shuffled Frog leaping Algorithm

Shuffled Frog Leaping Algorithm (SFLA) is a post heuristic computing technology of swarm intelligence proposed by Eusuff and Lansey in 2006. As a new biological evolution algorithm, it the advantages of mimetic algorithm(MA) and particle swarm optimization (PSO), that is simple concept, few parameters, fast calculation, strong global optimization ability and easy realization, etc.

The whole frog population of the wetland is divided into several sub-populations. Different sub-populations are considered as frog sets with different thoughts. Frogs in subpopulation execute local area deep-searching in solution space according to certain strategy. In sub-population every frog has its own thought and is affected by other frogs while evolving with the evolution of sub-population. After the defined local search iteration number is over, thoughts are exchanged in subpopulation mixing process. The balance strategy between global information exchange and local area deep-searching makes SFLA leap out of local extremum and march towards the direction of global optimization.

In a D-d target searching space, generate randomly P frogs (solution) to compose initial population. The i[th] frog represents the solution of the problem $Xi= (x_{i1},x_{i2},...,x_{iD})$. Frogs are arranged good to bad according to fitness to divide the whole population into M sub-population. Among them, the frog ranking 1st is divided into 1st sub-population, one ranking 2nd into 2nd sub-population, one ranking Mth into Mth subpopulation, one ranking M+1th into M+1th sub-population, one ranking M+2th into M+2th sub-population, analogize in sequence until all frogs have been divided.

Every sub-population is used for local area deep-searching, that is in every time of iteration of sub-population, the worst individual X_w , the best one X_b and global best one X_g of subpopulation in this iteration are determined first. Update operation is just done to current the worst individual X_w , of which the update strategy is

Frog leaping step update:

Position change $(Di) = rand\ () * (X_b-X_w)$ (2)

Location update:

New position X_w = current position $X_w + D_i$; $D_{max} \leq Di \leq -D_{max}$ (3)

Where $rand()$ represents random number uniformly distributed between 0 and 1; max D represents the allowed update step maximum. If the fitness value of $newX_w$ is good enough, X_w will be replaced. If it isn't improved, then

$(Di) = rand\ () * (X_g-X_w)$ $D_{max} \leq Di \leq -D_{max}$ (4)

If the fitness value of $newX_w$ still hasn't been improved, a new X_w will be generated randomly. Repeat this update operation until satisfying update algebra.

After the local area deep-searching of all sub-populations have been finished, all frogs in whole sub-population are mixed ordered anew into sub-populations. Then local area deep searching is processed until satisfying mixed iteration number (Fig. 1)

4. SFLA-ANN Based Soft sensor Results

In this study, an artificial neural network was used to build a soft sensor to predict the permeability of the reservoir by using log data. The best ANN architecture was: 5-7-1 (5 input units, 7 hidden neurons, 1 output neuron). ANN model trained with back propagation network (Fig. 2) was trained by Levenberg-Marquardt to predict permeability using five parameters (CT, DT, NPHI, RHOB, GR) as inputs. The transfer functions in hid-den and output layer are sigmoid and linear, respectively.

SFLA is used as neural network optimization algorithm and The Mean Square Error (MSE) used as a cost function in this algorithm. The goal in proposed algorithm is minimizing this cost function. Every weight in the network is initially set in the range of [-1, 1] and every initial particle is a set of weights generated randomly in the range of [-1, 1].

We used 900 data samples were chosen by a random number generator for network training. The remaining 500 samples were put aside to be used for testing the network's integrity and robustness.

The permeability prediction of the reservoir in the training and test phase are shown in Figures 3 and 4, respectively. The simulation performance of the SFLA-ANN based soft sensor model was evaluated on the basis of mean square error (MSE) and efficiency coefficient R^2. 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 SFLA-ANN based soft sensor is better than ANN based soft sensor. 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 . Figures 5 and 6 show the extent of the match between the measured and predicted permeability values by SFLA-ANN and ANN based soft sensor in terms of a scatter diagram.

Table 1: Comparison between the performances of SFLA-ANN and ANN based soft sensor

	SFLA-ANN	ANN
MSE	0.0054071	0.01568
R^2	0.92405	0.85309

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Pseudo code of the Shuffled Frog Leaping (SFL)
Begin;
  Randomly generate a population (P) of solutions (frogs);
  For each individual (frog); calculate fitness of i th frog;
  Sort the population in descending order of their fitness;
  For i = 1 to number of generations;
    Divide P into m memeplexes;
    For each memeplex;
      Determine the best and worst frogs;
      Repeat
        Improve the worst frog position using equation (1) or (2);
      Until a specific number of iterations is satisfied;
    End for;
  End for;
  Combine the evolved memeplexes;
  Sort the population P in descending order of their fitness;
  Check if termination = true;
End;
```

Figure 1: Pseudo code of the Shuffled Frog Leaping

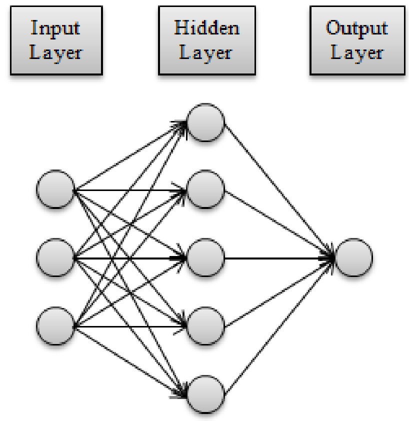
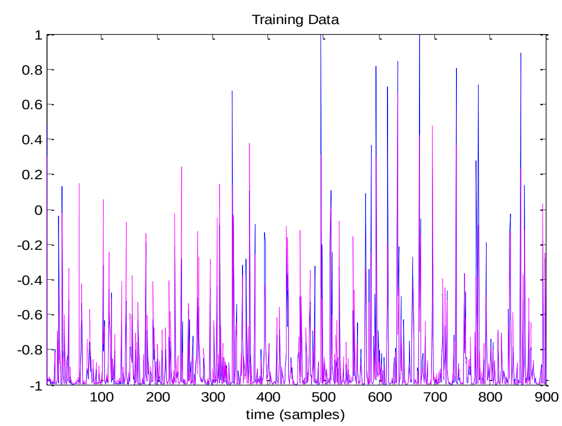
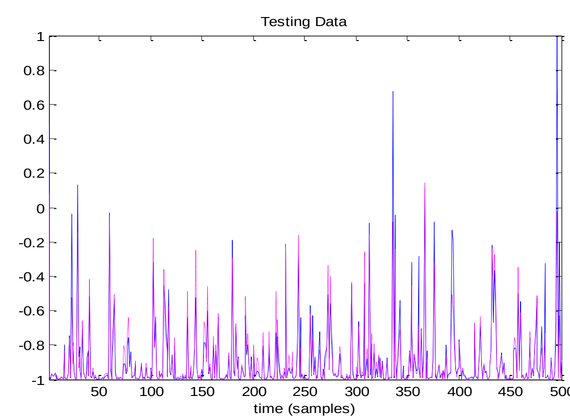


Figure 2: Architecture of three layer ANN

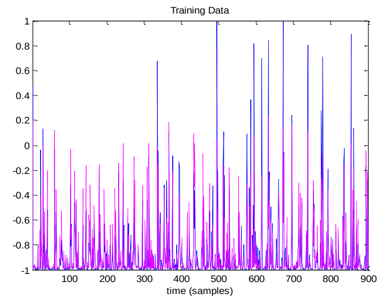


(a)

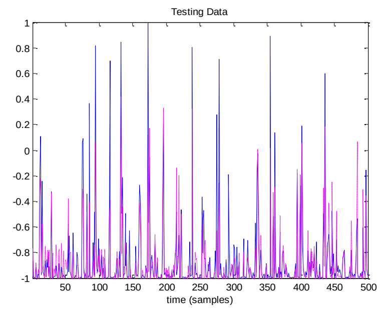


(b)

Figure 3: Comparison between measured and predicted permeability (SFLA-ANN): a)Training b)Test



(a)



(b)

Figure 4: Comparison between measured and predicted permeability (ANN): a) Training b) Test

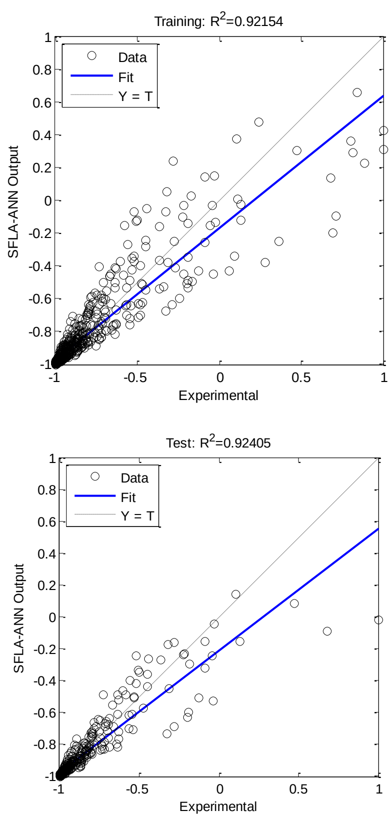


Figure 5: $\boldsymbol{R^2}$ SFLA-ANN based soft sensor

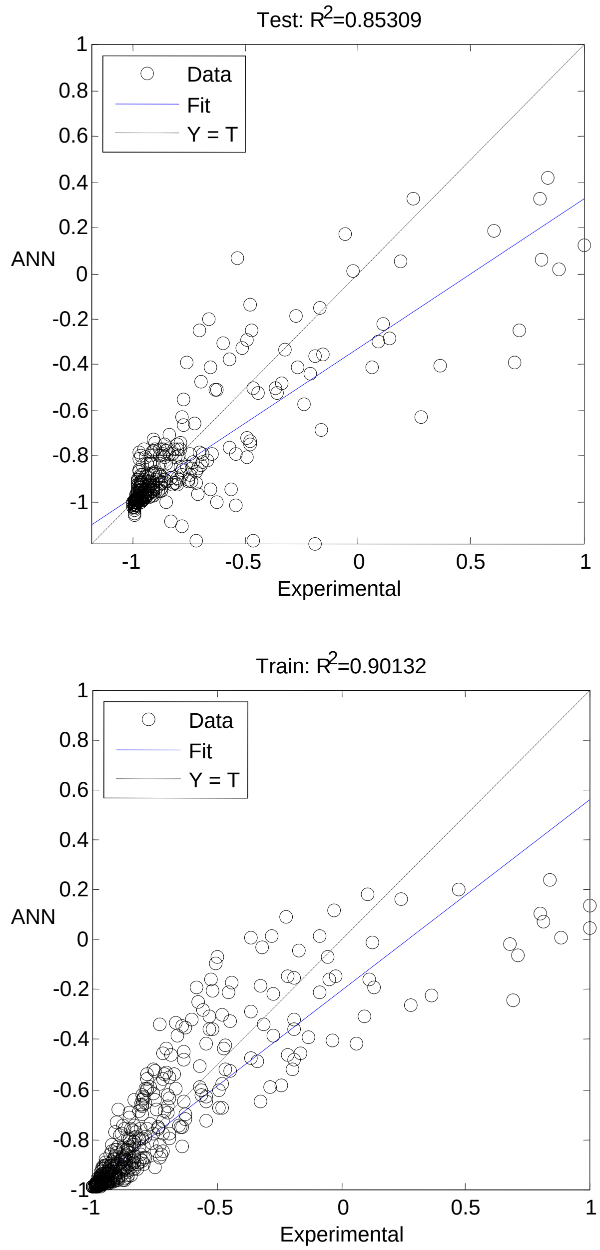


Figure 6: $\boldsymbol{R^2}$ ANN based soft sensor

5. Conclusion

1) SFLA-ANN based soft sensor is successfully demonstrated on permeability estimation.
2) Shuffled Frog-Leaping algorithm is a powerful optimization technique, especially when the objective function has several local minima.
3) Other evolutionary algorithms combined with Shuffled Frog-Leaping algorithm can be used as soft sensor performance is better.

4) SFLA-ANN based soft sensor combines local and global searching ability of the back propagation and SFLA, respectively.

Acknowledgements:

Authors are grateful to the Petroleum University of Technology for support to carry out this work.

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References

1. Balan, B., Mohaghegh, S., Ameri, S. (1995),"State-of-the-art in permeability determination from well log data: part I-a comparative study, model development."In: SPE Eastern Regional Conference and Exhibition, West Virginia, pp. 17–21.,
2. Brown, M., & Harris, C. (1994), "Neural fuzzy adaptive modeling and control." Englewood Cliffs, NJ: Prentice-Hall.
3. Doveton, J.H., Prensky, S.E., (1992)"Geological applications of wireline logs: a synopsis of developments and trends." The Log Analyst 33 (3), 286–303.
4. Eusuff M. M, Lansey K.E, (2006) "Shuffled frog-leaping algorithm: A memetic meta-heuristic for discrete optimization, " Engineering Optimization.Vol.38, No.2, pp. 129-154,
5. Garcia-Pedrajas, N., Hervas-Martinez, C., & Munoz-Perez, J. COVNET: ,(2003), "A cooperative co-evolutionary model for evolving artificial neural networks." IEEE Transaction on Neural Networks,14, 575–596.
6. Holland J. H.,(1975), "Adaptation in Natural and Artificial Systems", University of Michigan Press, Ann Arbor, MI.
7. Hornick, K., Stinchcombe, M., & White, H. (1989). "Multilayer feed forward networks are universal approximators.", Neural Networks, 2, 359–366
8. Hornik, K., Stinchcombe, M., White, H.,(1990),"Universal approximation of an unknown mapping and its derivatives using multilayer feed forward networks." Neural Net w;3(5):551–60.
9. Juang, C. F.: (2004), "A Hybrid of Genetic Algorithm and Particle Swarm Optimization for Recurrent Network Design." IEEE Transactions on Systems, Man, and Cybernetics–Part B: Cybernetics, 34(2) , 997-1006
10. Qu1, X., Feng, J., Sun, W. ,(2008), "Parallel Genetic Algorithm Model Based on AHP and Neural Networks for Enterprise Comprehensive Business", IEEE Intl. Conf. on Intelligent Information Hiding and Multimedia Signal Processing, pp.897-900.
11. Rallo, R., Ferre-Gin, J., Arenas, A., & Giralt, F. (2002). Neural virtual sensor for theinferential prediction of product quality from process variables. Computers andChemical Engineering, 26, 1735–1754.
12. Rechenberg, (1965)," Cybernetic Solution Path of an Experimental Problem", Library Translation 1122, Royal Aircraft Establishment, Farnborough, Hampshire, UK.
13. Reed, R., (1993), "Pruning algorithms-a survey", IEEE Trans. Neural Networks Vol.4, pp.740–747.
14. Souto, M.C.P.de, Yamazaki, A., Ludernir, T.B., (2002). "Optimization of neural network weights and architecture for odor recognition using simulated annealing", Proc. 2002 Intl. Joint Conf. on Neural Networks,Vol.1, pp.547-552.