

APPLICATION OF ARTIFICIAL NEURAL NETWORKS TO PREDICT WETTABILITY AND RELATIVE PERMEABILITY OF SANDSTONE ROCKS

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ABSTRACT

An Artificial Neural Network (ANN) model based on the back-propagation technique is trained with a number of variables from experimentally established relative permeability curves. The reservoir core input data covers an extensive range of porosities and permeabilities from different sandstone lithologies having diverse wettabilities. The trained model is then tested with only a couple of input variables such as the initial connate water saturation, S_{wc} and the residual oil saturation, S_{or} . The developed model outputs, or the predictions define the relative permeability end-points and the intersection point to quantify the wettability and the shape of the relative permeability curves. A number of correlations based on empirical models and network models exist to predict the relative permeability curves and the wettability of oil bearing sandstone formations from the initial oil and water. Calculations from the ANN model were then compared with values calculated from other models currently in wide spread use.

NOMENCLATURE

ANN	:	Artificial Neural Network,
BP	:	Back-propagation paradigm,
S_{wc}	:	connate water saturation,
S_{or}	:	residual oil saturation,
S_{int}	:	water saturation at the intersection point of the two curves,
$k_{ro} @ S_{wc}$:	end-point oil relative permeability at connate water condition,
$k_{rw} @ S_{or}$:	end-point water relative permeability at residual oil saturation,
k_{int}	:	the relative permeability at intersection of the two curves.

INTRODUCTION

Relative permeability and wettability are the two most important parameters in reservoir engineering. They describe the flow of different fluid phases in any reservoir and directly relate the distribution of fluid phases present, including the recovery of hydrocarbons. Therefore, the relative permeability curves along with the wetting preferences of the rock-fluid system define the reservoir flow mechanics, and hence the economics of any field development.

Artificial neural network (ANN) models are designed to emulate human information processing capabilities such as knowledge, speech, prediction and control. The ability of ANN systems to spontaneously learn from examples, reason over inexact and fuzzy data, and provide adequate responses to new information not previously seen, has generated increasing acceptance for this technology in the engineering and applied sciences, and resulted in numerous applications. Artificial neural networks are relatively new to the Geosciences and Petroleum Reservoir Engineering (1). This new approach has only been sparsely demonstrated in well testing (2), pump card diagnosis (3), well log analysis (4), performance of oilfield cements (5) and a few other applications. The use of this novel technology is presented towards predicting wettability and relative permeability data of hydrocarbon reservoirs.

RELATIVE PERMEABILITY AND WETTABILITY

Relative permeability defines the flow of one fluid phase in the presence of one or more fluids, the fluid phases being typically oil, water and gas. An elegant review of two-phase and three-phase relative permeability has been presented by Honarpour, Koederitz and Harvey (6). The relative permeability data are used extensively in commercial reservoir simulators to assess the reservoir performance or recovery scenarios, prior to full field development. The accuracy of the relative permeability curves are of paramount importance in terms of both reducing costs and uncertainty of the assessed reservoirs. Relative permeability data are conventionally obtained either from core analysis or are approximated from a number of conventionally established correlations depending on the formation characteristics.

Wettability describes the relative attraction of one fluid for a solid in the presence of other immiscible fluids, and is known to influence a number of other important reservoir parameters, including relative permeability. It is the main factor responsible for the microscopic fluid distribution in porous media and it

determines to a great extent the amount of residual oil saturation and the ability of a particular phase to flow. The relative affinity of a rock to a hydrocarbon in the presence of water is often described as 'water-wet', 'intermediate', or 'oil-wet'. Wettability, therefore, influences the overall hydrocarbon recoveries and the choice of appropriate improved recovery techniques.

Measurement and quantification of wettability is the subject of numerous research publications, and is reviewed by Anderson in a series of publications (7). However, as a general rule, experimentally established by Craig (8), a water-wet reservoir system will tend to have the intersection of the oil/water relative permeability curves at saturations greater than 50%, with $k_{rw} @ S_{or}$ less than 0.3, and an irreducible water saturation (or initial connate water saturation) S_{wc} of greater than 20%. An oil-wet system, however, will tend to have the intersection point at saturation greater than 50%, with $k_{rw} @ S_{or}$ greater than 0.5 or approaching 1.0, and a S_{wc} value of usually less than 15%. Wettability in the context of the present work is thus related in terms of the position of the point of intersection of the predicted relative permeability curves, i.e. the points S_{int} and k_{int} .

CORRELATIONS TO PREDICT RELATIVE PERMEABILITIES OF RESERVOIRS

Relative permeability data are usually obtained from laboratory investigations on suitable cores. However, this source may be lacking and suitable approximations must be derived. These approximations are determined for and depend on the process which the reservoir is undergoing. Most relative permeability mathematical models may be classified under the following categories: capillary models, statistical models, empirical models and network models. The advantages and limitations of each of the model are reviewed by Honarpour and co-workers (6).

The correlations for predicting relative permeability data are being increasingly used in reservoir simulators due to lack of real data at the start of any field development, and the costs incurred in generating such data. Further, complications may arise in terms of obtaining representative core data, the scaling of the core data to field data, and the accuracy of the ensuing data. Three correlations for approximating relative permeability data are often used in the industry due to their simplicity and limited input data requirements: Corey (9), Naar-Henderson (10) and that of Honarpour et al.(11) (henceforth referred to as Honarpour correlation). The Corey approximation is usually good for drainage processes, e.g. a gas drive where the saturation of the wetting phase is being decreased. The Naar-Henderson approximation is good for imbibition

processes, e.g. water drives where the saturation of the wetting phase is increasing. Honarpour developed a set of empirical prediction equations for water/oil imbibition relative permeability and gas/oil drainage relative permeability from a large number of experimental data.

The equations developed by Honarpour have not been extensively tested. However, most of the tests which have been made indicated that the equations are in closer agreement with laboratory data than the predictions of published correlations which were used as a basis for comparison. A reservoir engineer usually goes through a trial and error process to choose the appropriate relative permeability curves to best represent the reservoir system under study. This trial and error process is explored further in history matching when the correct relative permeability curve is being sought to match the reservoir performance.

DEVELOPMENT OF THE ARTIFICIAL NEURAL NETWORK MODEL

Artificial neural networks are network models that are based on the neural structure of the human brain (12). Maren and co-workers (13) have described ANN as computational systems, either hardware or software, which mimic the computational abilities of biological systems by using large numbers of simple, interconnected artificial neurons. Artificial neurons are simple emulations of biological neurons; they take in information from sensor(s) or other artificial neurons, perform very simple operations on this data, and pass results on to other artificial neurons. Neural networks operate by having their many artificial neurons process data in this manner. They use both logical parallelism (for all neurons in the same layer), combined with serial operations (as information in one layer is transferred to neurons in another layer).

The main aspect of ANN which makes them different from optimisers, conditional simulators, etc., is that they are data driven whereas optimisers etc., are model driven. Therefore, Neural networks can yield unbiased answer (or prediction). This is of immense advantage in the confidence levels of ANN although the same feature can be a disadvantage if data used for training are scarce or inaccurate.

A well defined two-phase relative permeability curve, such as that of water/oil (figure 1) can be usually described by the following six parameters: S_{wc} , S_{or} , S_{int} , k_{ro} @ S_{wc} , k_{rw} @ S_{or} , and k_{int} (as defined in the Nomenclature).

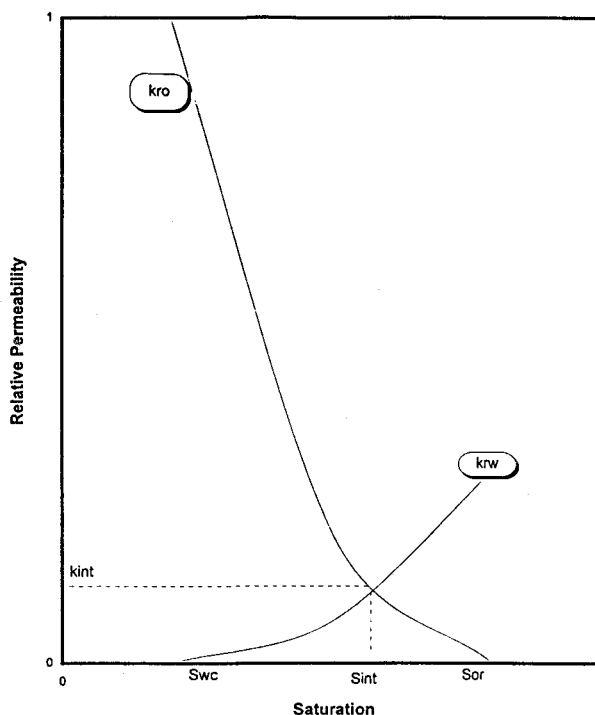


Fig. 1. Input and output parameters used in ANN model

Of these parameters, the connate water saturation (S_{wc}) and the residual oil saturation (S_{or}) can be easily obtained from resistivity logs (14), and are thus chosen as input parameters to the proposed ANN architecture. The other parameters: S_{int} , $k_{ro} @ S_{wc}$, $k_{rw} @ S_{or}$, and k_{int} are usually obtained through costly experimental work or extensive calculations; hence, they are chosen as output from the model. The ANN architecture for the proposed model is shown in figure 2. As illustrated by this figure, the network is composed of many simple processing elements that are organized into a sequence of layers. These are the input layer, the hidden layer, and the output layer.

The input and output layers, generally, consist of one or more hidden layers. There is no direct and precise way of determining the number of hidden layers to use and the exact number of neurons to include in each hidden layer. Research (15,16) in this area proved that one or two hidden layers with an adequate number of neurons is sufficient to model any solution surface of practical interest. The number of hidden neurons is a function of the problem complexity, the number of input and output parameters, and the number of training cases available. Hence, a trial and error process was used to determine

the number of hidden neurons. After trying a number of different configurations of hidden neurons, it was found that seven neurons in the hidden layer yielded the best results.

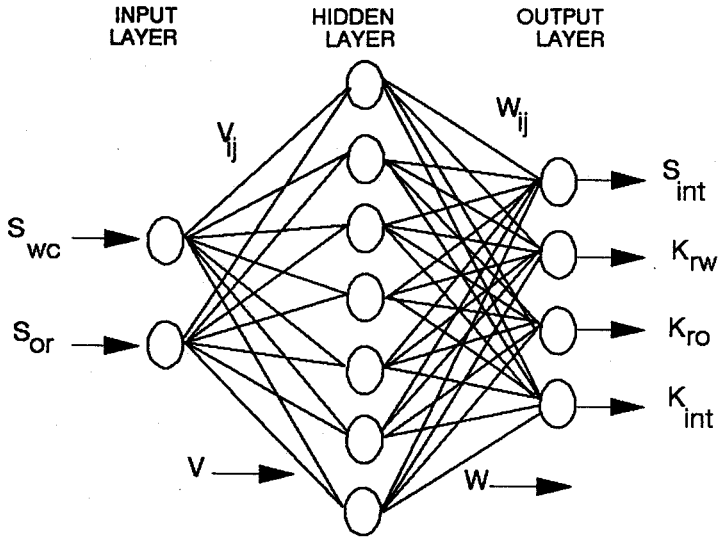


Fig. 2. The architecture of the ANN model-1

DATA PREPARATION AND NETWORK TRAINING

The developed ANN model has to be trained to recognize the relationships between the input parameters (S_{wc}) and (S_{or}) and the desired output parameters S_{int} , k_{ro} @ S_{wc} , k_{rw} @ S_{or} , and k_{int} . These relationships will be stored as connection weights between the different neurons. The process of determining the weights is called the training or the learning process. In order to train the ANN model to produce the desired output, the model has to be trained over the full range of the typical input parameters. The S_{wc} and S_{or} ranges used are between 0.0 and 1.0. Patterns within these ranges are evenly distributed so that the training can cover all possible typical load values. If this is not the case, training will tend to focus on regions where training patterns are densely clustered, and neglect those that are sparsely populated, hence, producing inaccurate results.

The multilayer feedforward network used in this work is trained using the backpropagation (BP) paradigm developed by Rumelhart and McVllland (17).

The BP algorithm uses the supervised training technique. In this technique, the interlayer connection weights and the processing elements thresholds are first initialized to small random values. The network is then presented with a set of training patterns, each consisting of an example of the problem to be solved (the input) and the desired solution to this problem (the output). In training the proposed model, 56 cases covering a wide range of porosities and permeabilities, and having diverse wettabilities were used. These data are generated from experimentally established relative permeability curves for different sandstone lithologies obtained primarily from the published literature, and to a limited extent from the local oil companies. Typical examples of the different training patterns used as part of the training data set are shown in table 1. These training patterns are presented repeatedly to the ANN model, and weights are adjusted by small amounts that are dictated by the general delta rule (17). This adjustment is performed after each iteration when the network's computed output is different from the desired output. This process continues until weights converge to the desired error level or the output reaches an acceptable level. The system of equations that provides a generalized description of how the learning process is performed by the BP algorithm is described by Simpson (18).

Table 1. Sample of Training Data Set Used

Case #	S_{wc}	S_{or}	$k_{ro} @ S_{wc}$	$k_{rw} @ S_{or}$	S_{int}	k_{int}
1	0.40	0.35	0.60	0.06	0.62	0.04
6	0.23	0.40	0.80	0.42	0.35	0.17
11	0.06	0.24	0.75	0.32	0.64	0.15
21	0.15	0.29	1.00	0.40	0.48	0.16
33	0.24	0.00	0.85	1.00	0.82	0.16
40	0.19	0.20	0.81	0.40	0.53	0.14
46	0.18	0.30	0.90	0.34	0.50	0.18
50	0.00	0.05	1.00	1.00	0.36	0.44

The training process of this ANN model was performed using the NeuroShell™ simulator. After a training period of 3 hours and 20 minutes, the network converged to a threshold of 0.01. Having trained the network successfully, the next step is to test the network in order to judge its performance.

NETWORK TESTING AND VALIDATION

The developed ANN model was tested with six sets of experimentally determined relative permeability curves, with a range of wettability characteristics. These data set consisted of a wide variation of input and output parameters as defined in figure 2, and were not used in the training of the model.

Figures 3 and 4 show the ANN predictions for position of the intersection point of the relative permeability curves. The figures also show the actual test data and those obtained by the different correlations for the same cases. It is evident that ANN gave extremely good predictions for the wettability, which in two of the test cases were identical to the model predictions. Statistical analysis of the results (see table 2) show that the developed model can predict wettability within an average R^2 of 0.938 and a mean absolute error of 2.57 %. This means that the model can explain 93.8 % of the variability in S_{int} (used to define wettability) of the selected input variables. This compares with the R^2 of 0.886 from the Honarpour correlation; the latter being the best one can obtain from the published correlations. The Corey and the Naar-Henderson correlations gave rather poor R^2 values of 0.015 and 0.024, respectively.

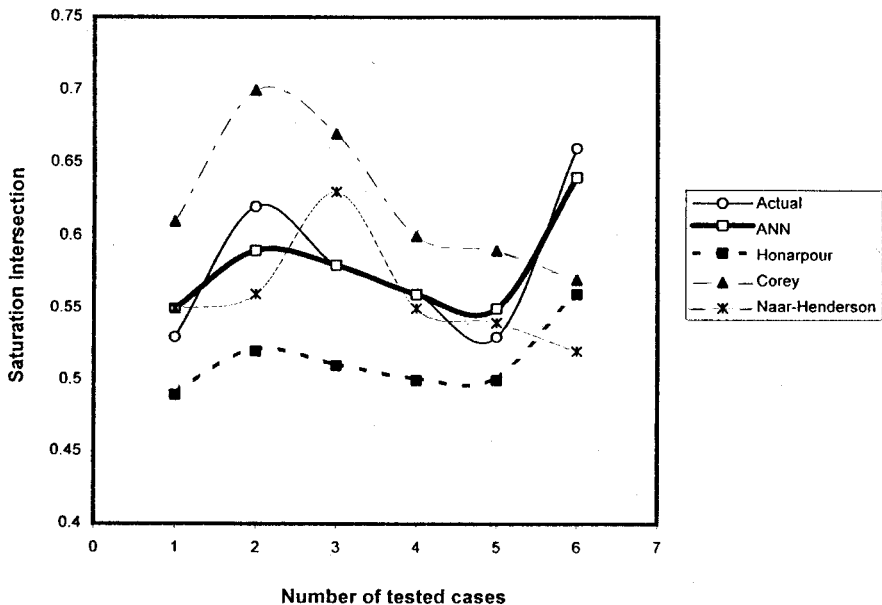


Fig. 3. Wettability results

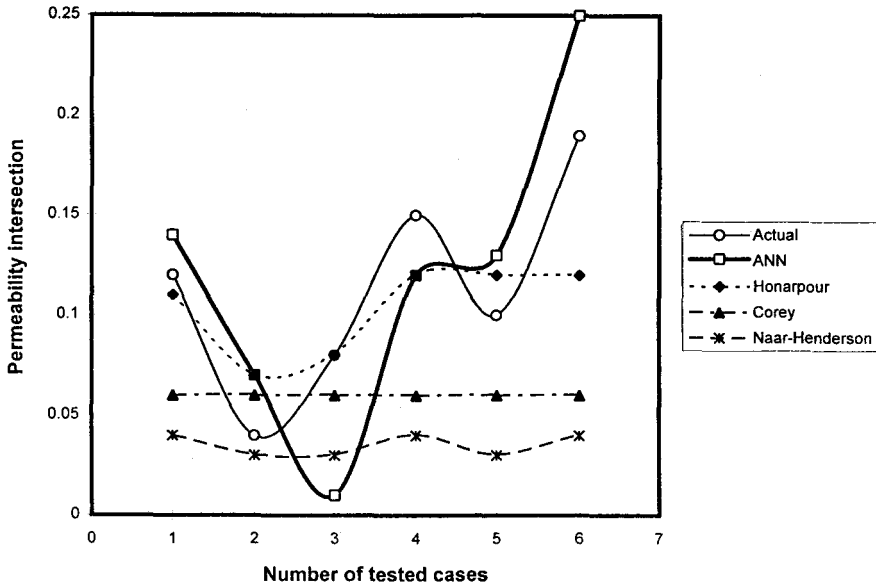


Fig. 4. Permeability intersection results

Table 2. Statistical Error Comparison for S_{int} Using ANN Model #1 and Others

Statistical Parameter	COREY	HNRPOR	NAARH	ANN
Mean Absolute Deviations (MAD)	0.0057	0.0052	0.0044	0.0003
Mean Squared Error (MSE)	0.0057	0.0052	0.0044	0.0003
Mean Absolute Percentage Error (MAPE)	12.096	12.726	8.836	2.603
Coefficient of Determination (R^2)	0.847	0.882	0.156	0.951

COREY: Corey's Equation

NAARH: Naar-Henderson Equation

HNRPOR: Honarpour Equation

ANN: Artificial Neural Network

The k_{int} as observed in figure 4 gave an average R^2 of 0.653 with the developed ANN model (Table 3). Although the k_{int} is insignificant in defining wettability, it has an importance in defining the overall shape of the relative permeability curves. Our results (19) show that k_{int} can be more accurate if the developed model was based on four input variables as shown in figure 5, rather than the two input variables used. The R^2 value of k_{int} then improves to 0.900, and the mean absolute error shows a marked improvement from 25 % to 20 %.

The four input model, therefore, gives better predictions for the intersection relative permeability value. However, incorporation of this model will require additional input data, and consequently increased costs.

Table 3. Statistical Error Comparison for K_{int} Using ANN Model #1 and Others

Statistical Parameter	COREY	HNRPOR	NAARH	ANN
Mean Absolute Deviations (MAD)	0.0052	0.0012	0.0081	0.0012
Mean Squared Error (MSE)	0.0052	0.0012	0.0081	0.0012
Mean Absolute Percentage Error (MAPE)	91.670	25.198	191.667	25.267
Coefficient of Determination (R^2)	0.0034	0.764	0.663	0.653

COREY: Corey's Equation
 HNRPOR: Honarpour Equation

NAARH: Naar-Henderson Equation
 ANN: Artificial Neural Network

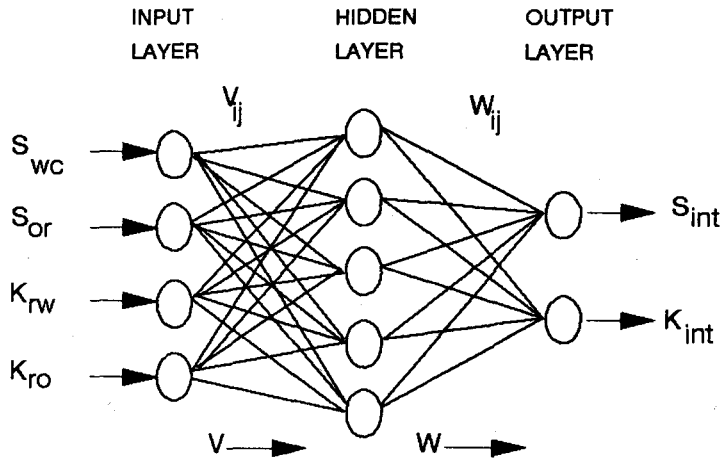


Fig. 5. The architecture of the ANN model-2

The measured end-point relative permeabilities, k_{rw} and k_{ro} , are shown in figures 6 and 7 with the predictions of the developed ANN model (with two inputs) and the chosen correlations. The developed model gave quite good predictions for the k_{rw} and k_{ro} in five out of the six test cases, with R^2 values of 0.939 and 0.484, respectively. The Corey and the Naar-Henderson correlations gave very poor predictions for the end-point relative permeabilities and were considered statistically insignificant for the sandstones tested. This was

Application of Artificial Neural Networks

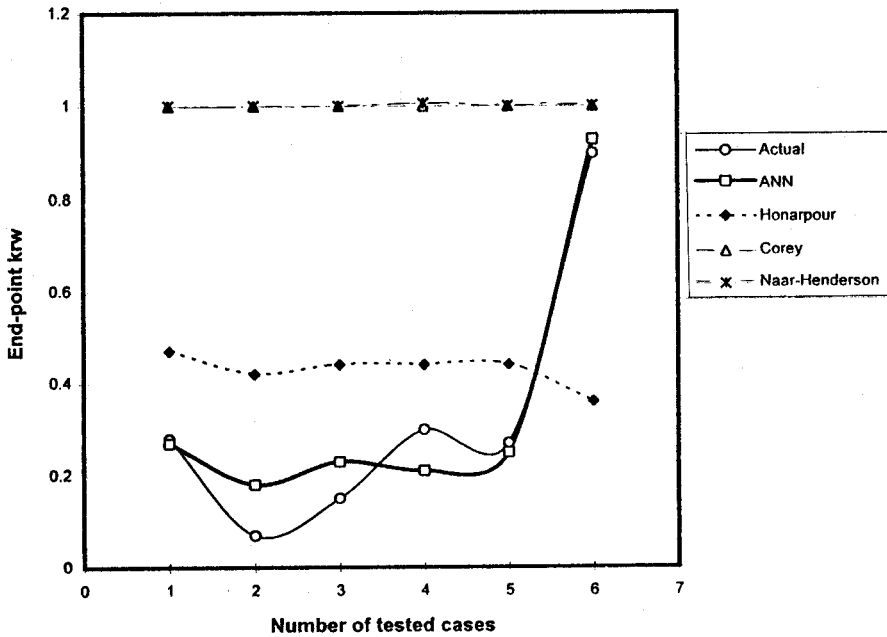


Fig. 6. End-point water relative permeability results

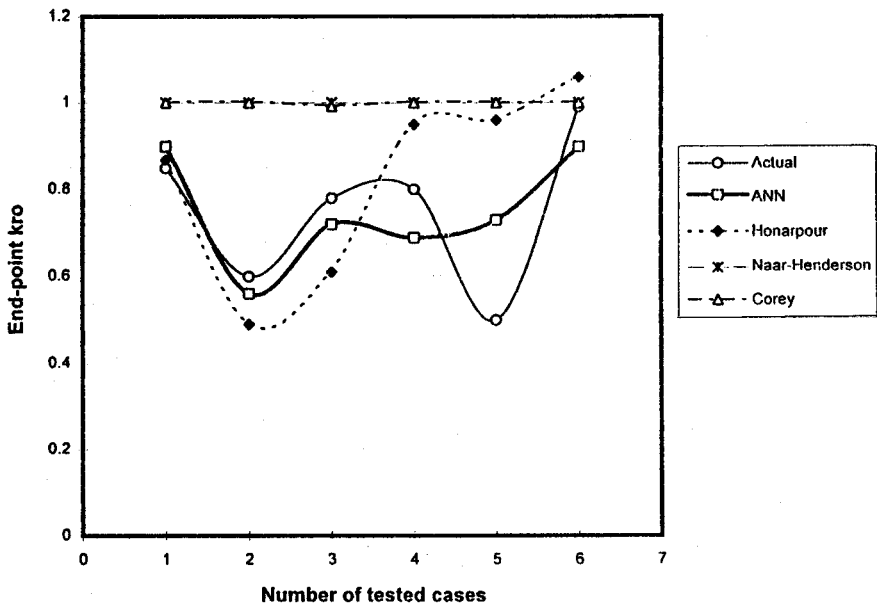


Fig. 7. End-point oil relative permeability results

explicable with the Corey equation being suitable for drainage processes (with gas drive) while Naar-Henderson being more suited to water drive imbibition processes (20), unlike the two-phase water/oil relative permeability data used in the presented training. The Honarpour correlation, however, gave reasonably good predictions for both the end-points, with R^2 values of 0.594 and 0.153, respectively. Although this is consistent with Honarpour's assertion that their model is based on numerous data, it is statistically poorer than the predictions of the developed ANN model.

The reasonably good ANN predictions is promising to the overall capability of the developed model, given the limitations of the training data set in terms of diverse lithologies and wettabilities. Preliminary studies (21) also showed improved ANN predictions when the training data were limited to a specific formation and field.

CONCLUSIONS

Artificial neural networks show promising results in predicting wettabilities and end-point relative permeabilities of sandstone formations. The robustness of the predictions can be greatly enhanced if the ANN model is trained and tested with data from similar lithology and formation characteristics. ANN model predictions can be significantly reduce the costs and uncertainties associated in obtaining relative permeability data currently used in reservoir simulators.

As ANN models are data driven, the higher the number of cases involved in training, the better the model predictions for wettabilities and relative permeabilities. The best methods to determine the minimum number of hidden nodes were found to be by trial and error process, with data quality being of utmost importance in the ensuing models.

ANN models show a far better prediction of the wettability and end-point relative permeabilities than the currently available correlations. This situation is primarily due to the ability of the neural networks to recognize both linear and non-linear relationships among the different variables which influence wettability and relative permeability of hydrocarbon reservoirs.

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REFERENCES

1. **Mohaghegh, S., 1995.** Neural Network: What it can do for petroleum engineers, JPT, Vol. 47, No. 1, pp.42-44.
2. **Al-Kaabi, A. A., and Lee, W. J., 1993.** Using Artificial Neural Nets to Identify the Well-Test Interpretation Model, Transactions SPE 20332, SPEFE, Vol. 8, No. 5. pp. 233-240.
3. **Ashenayi, K., et al. , 1994.** Application of ANN to Pump Card Diagnosis, SPECA, Vol. 6, No. 2.
4. **Mohaghegh, S., Arefi, R. and Ameri, S., 1995.** Design and Development of an ANN for Prediction of Formation Permeability, SPECA, Vol. 7, No. 2, pp.151-156.
5. **Fletcher, P., et al., 1995.** Predicting Quality and Performance of Oilfield Cements with ANN and FTIR Spectroscopy, JPT, Vol. 47, No. 2.
6. **Honarpour, M. M., Koederitz, L. F., and Harvey, A. H., 1986.** Relative Permeability of Petroleum Reservoirs, CRL Press Inc., Florida, USA.
7. **Anderson, W. G., 1987.** Wettability Literature Review, Parts 1-6, JPT November 1986 - December 1987.
8. **Craig Jr., F. F., 1971.** The Reservoir Engineering Aspects of Waterflooding, SPE Monograph, Dallas, USA.
9. **Corey, A. T. et al., 1956.** Three Phase Relative Permeability, Trans. AIME, Vol. 207, pp.349-355.

10. Naar, J., Wygal, R. J., and Henderson, J. H., 1962. Imbibition Relative Permeability In Unconsolidated Porous Media, SPEJ, AIME 11-13.
11. Honarpour, M. M., Koederitz, L. F., and Harvey, A. H., 1982. Empirical Equations for Estimating Two Phase Relative Permeabilities in Consolidated Rocks, Trans. AIME, Vol. 279, pp 2905.
12. Stanley, J., 1990. Introduction to Neural Networks, Third edition, Sierra Madre, California :California Scientific Software.
13. Maren, A. J., Harston C. T., and Pap, R. M., 1990. Handbook of Neural Computing Applications, Academic Press Inc., San Diego.
14. Schlumberger Education Services, 1989. Schlumberger Log Interpretation Principle/Applications, Houston, Texas 77023, USA.
15. Hechr-Nielsen, R., 1989. Theory of Backpropagation Neural Network, Proceedings of the International Joint Conference on Neural Networks, IEEE, Washington DC, Vol. 1, pp. 593-605.
16. Lapedis, A., and Forber, R., 1988. How Neural Network Works, Neural Information Processing Systems, American Inst. of Physics, pp 442-456.
17. Rumelhart, D. E., and McVlelland, J. L., 1986. Parallel Distribution Processing: Exploration in the Microstructure of Cognition, Vol. 1, Foundations, MIT Press.
18. Simpson, P. K., 1990. Artificial Neural Systems: Foundations, Paradigms, Applications and Implementations, First Edition, Pergamon Press Inc., NY.
19. Al-Alawi, S. M., Kalam, M. Z., and Al-Mukheini, M., 1995. Predicting Sandstone Wettability and Relative Permeability Using ANN, Vol. 10, pp. 242-251, Proceedings of the Fourth Al-Azhar Eng. International Conference.
20. Crichlow, H. B., 1972. Modern Reservoir Engineering: A simulation approach, Prentice - Hall Inc., New Jersey, pp. 21-39.

21. **Kalam, M. Z., Al-Alawi, S. M., and Al-Mukheini, M., 1995. The Application of ANN to Predict End-Point Relative Permeabilities and Wettability of a Limestone Reservoir in Middle East, Paper UAEU/SPE 95-6, Proceedings for Regional Symposium on 'Improved Oil Recovery,' UAE, pp. 71-80.**