Modular Artificial Neural Network for Prediction of Petrophysical Properties From Well Log Data

Chun Che Fung, *Member, IEEE*, Kok Wai Wong, *Member, IEEE*, and Halit Eren, *Member, IEEE*

***Abstract*— An application of Kohonen's self-organizing map (SOM), learning-vector quantization (LVQ) algorithms, and commonly used backpropagation neural network (BPNN) to predict petrophysical properties obtained from well-log data are presented. A modular, artificial neural network (ANN) comprising a complex network made up from a number of subnetworks is introduced. In this approach, the SOM algorithm is applied first to classify the well-log data into a predefined number of classes. This gives an indication of the lithology in the well. The classes obtained from SOM are then appended back to the training input logs for the training of supervised LVQ. After training, LVQ can be used to classify any unknown input logs. A set of BPNN that corresponds to different classes is then trained. Once the network is trained, it is then used as the classification and prediction model for subsequent input data. Results obtained from example studies using the proposed method have shown to be fast and accurate as compared to a single BPNN network.**

***Index Terms*—Learning vector quantization, modular, neural networks, petrophysical, self organizing map, well log.**

I. Introduction

The two main issues in evaluating reservoir data using well logs are characterization of rock formation and prediction of petrophysical properties. In the literature, a large number of techniques have been introduced to establish adequate evaluation models [1]. However, the task is not all that simple for two reasons: 1) the complexities of many different factors influencing the log responses and 2) increasing amount of downhole measurements employed [1]. Traditionally, derivation of such interpretation models normally falls into two main approaches: graphical crossplotting/statistical techniques and multivariate statistical methods such as principal component analysis and cluster analysis. Although both approaches are used extensively, they have inherent shortcomings. Most of the time, it is difficult to determine any theoretical or empirical models for the accurate analysis of reservoirs.

In recent years, neural networks as an emerging technology have been applied to many areas of log evaluation. This new technique has proven to be more successful than the classical statistical methods [2], [3]. Most of the neural-network applications in this area are reported to be based on backpropagation neural networks (BPNN) [2]–[5] with some exceptions such as fuzzy ARTMAP [6], self-organizing map, and learning-vector quantization (LVQ) [7]. When BPNN is used as the interpretation model, the inputs to the network are taken from the data obtained from various logging instruments such as gamma ray, resistivity, neutron porosity, and bulk density devices. The outputs from BPNN correspond to different parameters such as rock matrices, porosity, and permeability. BPNN is essentially a supervised learning network. Therefore, a set of input and output vectors must be used to train the network. Of the entire learning algorithm, the error backpropagation method is the most widely used [8]. Although this algorithm has been successful in many applications, it has disadvantages such as the long training time that can be inconvenient in practical and on-line applications. This necessitates the improvement of the basic algorithm or integration with other forms of network configurations such as modular networks reported here.

In this paper, a modular neural-network based on self-organizing map (SOM), LVQ, and BPNN is used to predict the petrophysical properties from well-log data. As compared with the usual BPNN approach that uses only a single network, the modular network enables the division of a complex network into a number of subnetworks. This process is similar to the "genetic approach" [9] used for petrophysical properties prediction. Initially, the SOM and LVQ are used to classify the data that gives an indication of the lithology. Several BPNN's corresponding to the number of classes obtained from SOM are then trained for the purpose of prediction of petrophysical properties. Since the data to be handled by each subnetwork is effectively reduced, the training time is significantly shortened.

II. Artificial Neural Network

A. Self-Organizing Map

A SOM [10] performs unsupervised learning. It has the ability to learn and organize information without training data being provided. The SOM network consists of two layers of nodes and performs clustering through a competitive learning technique known as "winner-take-all." In terms of learning time, SOM network is fast as it uses single-pass learning rather than multiple feedback.

B. Learning Vector Quantization

The LVQ is closely related to SOM [10]. While SOM is an unsupervised learning network, LVQ is supervised. The other difference between the two is that LVQ has no

Manuscript received May 13, 1996. This work was supported by Crocker Data Processing Company.

The authors are with the School of Electrical and Computer Engineering, Curtin University of Technology, Kent Street, Bentley, W.A. 6102, Australia (e-mail: terenh@cc.curtin.edu.au).

Publisher Item Identifier S 0018-9456(97)09436-9.

defined neighborhood around the "winner" during learning. LVQ makes use of a competitive learning rule to define decision boundaries in the input space. Its main purpose is to define class regions in the input data space. In general, LVQ is known to be fast in learning and the classification accuracy is high.

C. Backpropagation Neural Network

BPNN is the most widely used neural network system and the most well-known supervised learning technique [8]. Basically, BPNN is comprised of three layers: input layer, hidden layers, and output layer. The backpropagation algorithm is a systematic method for training multilayer artificial neural network. The objective of training the BPNN is to adjust the weights between these layers so that the application of a set of inputs produces the desired set of outputs. The training speed of the BPNN is slow. Recently, researchers have reported different ways of accelerating the training process by modifying the basic BPNN algorithm [11].

III. Modular Artificial Neural Network

A typical application of BPNN in the prediction of petrophysical properties uses a single BPNN network. Data obtained from the input logs such as spontaneous potential, uninvaded zone resistivity, and gamma ray activity are normalized before applying them to the input layer of the BPNN. The output neurons are assigned to correspond to the petrophysical properties such as sandstone, limestone, and dolomite.

This paper proposes a modular neural network that integrates SOM, LVQ, and BPNN together to perform the lithology classification and prediction of petrophysical properties. The block diagram of the modular neural network is shown in Fig. 1. Further details of the proposed classification method in the block diagram, which comprises of SOM and LVQ, can be found in [7]. First, the unsupervised SOM is used to classify the training input logs and output parameters into a number of predefined classes. This classification from the SOM gives an indication of the lithology of the training well. The classes obtained from the SOM are then appended back to the training input logs for the training of the supervised LVQ. After training, the LVQ can then be used to classify any unknown input logs, according to the training classes.

A number of BPNN networks corresponding to the number of classes obtained from SOM are trained. After the classification process, the data fed into the different BPNN resembles similar characteristics. In this way, training of the BPNN is expected to take shorter time.

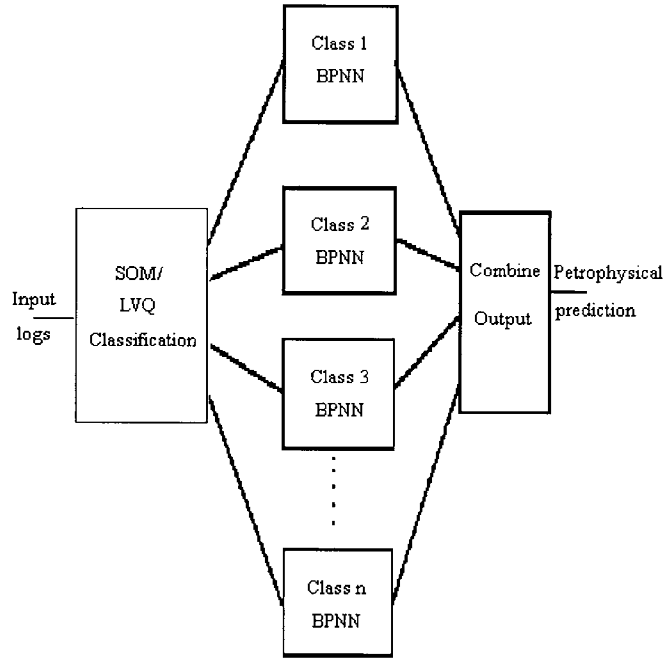

Fig. 1. Block diagram of modular neural network.

TABLE I
COMPARISON OF SINGLE BPNN AND MODULAR NEURAL NETWORK

	Modular Network	Single Network
BPNN Configuration	9 x 6 input neurons 5 hidden neurons 3 output neurons	6 input neurons 5 hidden neurons 3 output neurons
Training Time		
Network 1:	72 sec	
Network 2:	58 sec	
Network 3:	16 sec	
Network 4:	50 sec	
Network 5:	7 sec	
Network 6:	28 sec	
Network 7:	44 sec	
Network 8:	49 sec	
Network 9:	98 sec	
Total:	**7 minutes**	**34 minutes**
Mean Square Error		
Network 1:	0.001872	
Network 2:	0.0001	
Network 3:	0.000082	
Network 4:	0.0001	
Network 5:	0.000099	
Network 6:	0.0001	
Network 7:	0.0001	
Network 8:	0.0001	
Network 9:	0.0018	
Average:	**0.00048**	**0.0297**

IV. Case Results and Discussions

The hardware platform used for this work is a Pentium-90 PC. A set of data that contains 127 input logs and corresponding output properties has been used for training. Another set of 127 test data are used to examine the performance of the modular neural network which comprises SOM, LVQ, and BPNN. The results obtained are then used to compare with the traditional single BPNN network.

In this study, three output rock matrices are used to demonstrate the prediction ability of the proposed network. The rock matrices are (MAT-1) sandstone, (MAT-2) limestone, and (MAT-3) dolomite. The input logs are (RHOB) bulk density, (NPHI) neutron, (RT) uninvaded zone resistivity, (GR) gamma ray, (DT) sonic travel time, and (SP) spontaneous potential.

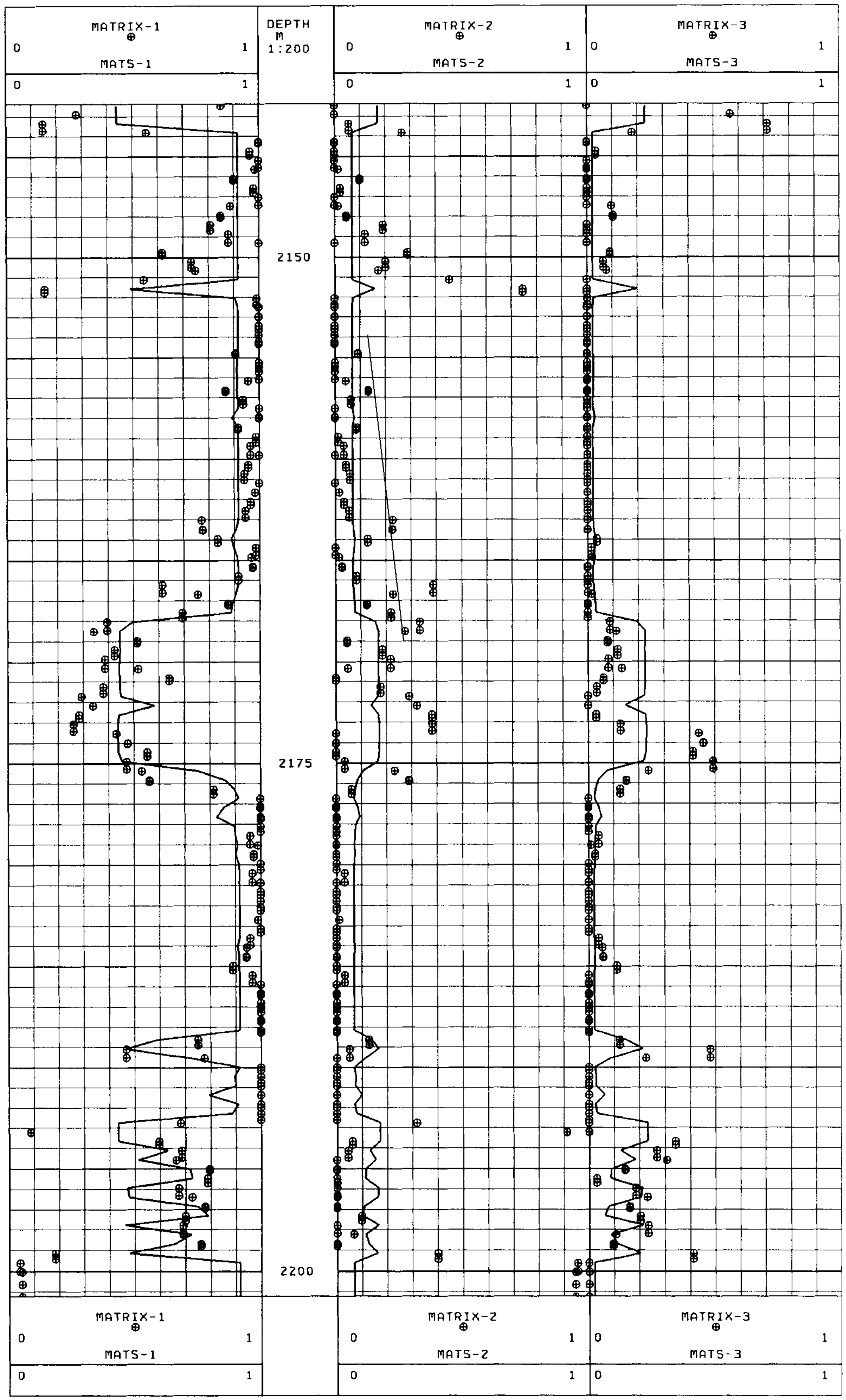

Fig. 2. Single BPNN output compared to core data.

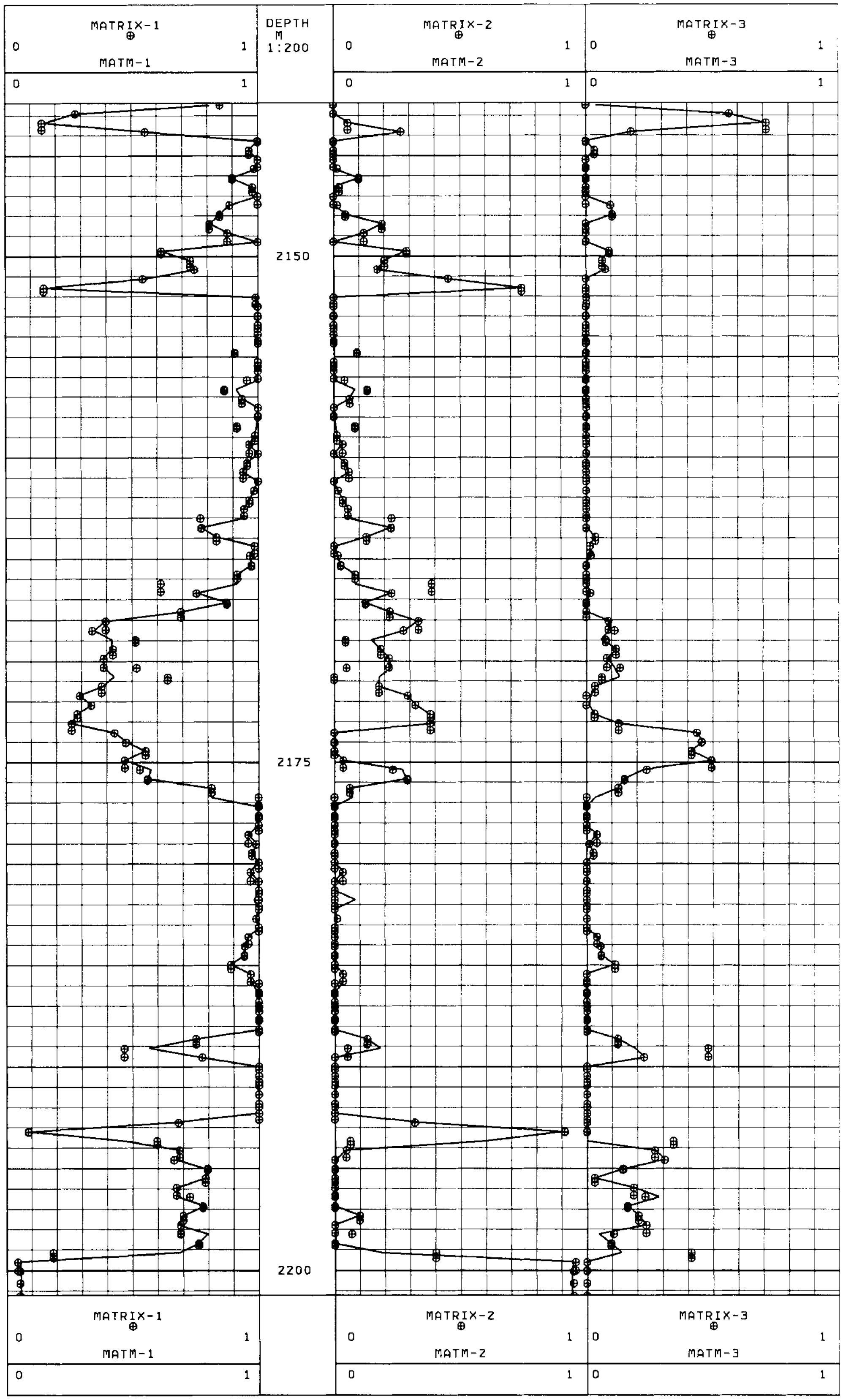

Fig. 3. Modular network output compared to core data.

The BPNN configuration chosen for the single network consists of six input neurons, five hidden neurons, and three output neurons. For the modular network, the SOM is initially used to classify the training data into nine different classes. Nine classes were found to be appropriately classifying the data. Then, these classes are attached to the input logs for the training of the LVQ network. The training data are also divided into the corresponding classes for training of individual BPNN networks. The BPNN configuration chosen for all the nine subnetworks is the same as the single BPNN network.

Table I shows the results obtained from modular-network as compared with the results from the single-network approach. As expected, the training time for the modular network is much shorter than for the single-network method. The overall accuracy of the modular network is also better based on the comparison between the mean-square errors. The mean-square error of the modular network is calculated by taking the average of the mean-square errors from the subnetworks. Fig. 2 shows the graphical plot of the results generated from the single BPNN as compared with the actual core data. The modular network's output are shown in the graphical plot in Fig. 3. From these figures, it can be observed that the modular network's output follows closely the desired output core data. The correlation between the neural network's output and the desired core data are calculated by a statistical method using the percent similarity coefficient. For single BPNN method, the percentage similarity for MAT-1, MAT-2, and MAT-3 are 92.4, 41.4, and 53.8, respectively. As for the modular neural network, the similarity is 98.7, 89.9, and 92.5, respectively. Again, these figures have given a clear indication that the modular neural network performs better than single BPNN.

V. Conclusion

A petrophysical prediction method based on a modular artificial neural network is proposed in this paper. SOM and LVQ algorithms have been used to classify the lithology of a given well from the input log data. After the classification process, a number of BPNN are then used. This approach of petrophysical prediction has shown to be more accurate as compared to the traditional single BPNN approach. Results from the case study have shown that the training time of this modular network is shorter. This reported approach could be used as an alternative method for petrophysical prediction in addition to the traditional methods.

Acknowledgment

The authors are grateful to Crocker Data Processing Company for the data provided for this research and the permission to publish this paper.

References

[1] E. R. Crain, *The Log Analysis Handbook Volume 1: Quantitative Log Analysis Methods.* New York: Penn Well, 1986.

[2] P. M. Wong, F. X. Jian, and I. J. Taggart, "A critical comparison of neural networks and discriminant analysis in lithofacies, porosity and permeability predictions," *J. Petroleum Geol.*, vol. 18, pp. 191–206, Apr. 1995.

[3] C. A. Goncalves, P. K. Harvey, and M. A. Lovell, "Application of a multilayer neural network and statistical techniques in formation characterization," in *SPWLA 36th Annu. Logging Symp.*, 1995.

[4] S. J. Rogers, J. H. Fang, C. L. Karr, and D. A. Stanley, "Determination of lithology from well logs using a neural network," *AAPG Bull.*, vol. 76, no. 5, pp. 731–739, 1992.

[5] J. L. Baldwin, D. N. Otte, and C. L. Wheatley, "Computer emulation of human mental processes: Application of neural network simulators to problems in well log interpretation," *Soc. Petroleum Eng.*, SPE paper 19619, pp. 481–493, 1989.

[6] P. M. Wong, I. J. Taggart, and T. D. Gedeon, "The use of fuzzy ARTMAP for lithofacies classifications: A comparison study," in *SPWLA 36th Annu, Logging Symp.*, 1995.

[7] C. C. Fung, K. W. Wong, H. Eren, and R. Charlebois, "Lithology classification using self-organizing map," in *Proc. IEEE Int. Conf. Neural Networks*, Perth, Australia, Nov./Dec. 1995, vol. 1, pp. 526–532.

[8] D. E. Rumelhart, G. E. Hinton, and R. J. Williams, "Learning internal representation by error propagated," in *Parallel Distributed Processing.* Cambridge, MA: MIT Press, 1986, vol. 1, pp. 318–362.

[9] F. X. Jian, C. Y. Chork, I. J. Taggart, D. M. McKay, and R. M. Barlett, "A genetic approach to the prediction of petrophysical properties," *J. Petroleum Geol.*, vol. 17, pp. 71–88, Jan. 1994.

[10] T. Kohonen, *Self-Organizing Maps.* Berlin, Germany: Springer-Verlag, 1995.

[11] S. T. Welstead, *Neural Network and Fuzzy Logic Applications in C/C++*. New York: Wiley.

Chun Che Fung (M'93), for photograph and biography, see this issue, p. 1283.

Kok Wai Wong (S'88–M'91) received the diploma in electronics and communications engineering in 1991 from Singapore Polytechnic, and the B.Eng. degree in computer engineering from Curtin University of Technology, Bentley, Australia. He is pursuing the Ph.D. degree at the School of Electrical Engineering, Curtin University of Technology.

His research areas include artificial neural networks, fuzzy logic, neuro-fuzzy, and their applications.

Halit Eren (M'87), for photograph and biography, see this issue, p. 1283.