NEURAL NETWORK PREDICTION OF PERMEABILITY IN THE EL GARIA FORMATION, ASHTART OILFIELD, OFFSHORE TUNISIA

J.H. Ligtenberg[*] and A.G. Wansink[*]

The Lower Eocene El Garia Formation forms the reservoir rock at the Ashtart oilfield, offshore Tunisia. It comprises a thick package of mainly nummulitic packstones and grainstones, with variable reservoir quality. Although porosity is moderate to high, permeability is often poor to fair with some high permeability streaks.

The aim of this study was to establish the relationships between log-derived data and core data, and to apply these relationships in a predictive sense to un-cored intervals. The main objective was to predict from measured logs and core data the limestone depositional texture (as indicated by the Dunham classification), as well as porosity and permeability. A total of nine wells with complete logging suites, multiple cored intervals with core plug measurements together with detailed core interpretations were available.

We used a fully connected Multi-Layer-Perceptrons network (MLP, a type of neural network) to establish possible non-linear relationships. Detailed analyses revealed that no relationship exists between log response and limestone texture (Dunham class). The initial idea to predict Dunham class and subsequently use the classification results to predict permeability could therefore not be pursued. However, further analyses revealed that it was feasible to predict permeability without using the depositional fabric, but using a combination of wireline logs and measured core porosity. Careful preparation of the training set for the neural network proved to be very important. Early experiments showed that low to fair permeability (1-35 mD) could be predicted with confidence, but that the network failed to predict the high permeability streaks. ”Balancing” the data set solved this problem. Balancing is a technique in which the training set is increased by adding more examples to the under-sampled part of the data space. Examples are created by random selection from the training set and white noise is added. After balancing, the neural network’s performance improved significantly. Testing the neural network on two wells indicated that this method is capable of predicting the entire range of permeability with confidence.

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INTRODUCTION

The reservoir rock in the Ashtart oilfield, offshore Tunisia, is composed of the Lower Eocene El Garia Formation of the Metlaoui Carbonate Group. The quality of this carbonate reservoir is variable. Although it has a moderate to high porosity, the permeability is poor to fair, generally below 10 mD (Loucks *et al.*, 1998; Fig. 6). The best reservoir intervals are characterized by high permeability streaks, which occur where interparticle porosity is preserved or at strongly dolomitised or fractured zones. This is predominantly dependent on a number of diagenetic processes such as mechanical compaction and dolomitization. According to Loucks *et al.* (1998), permeability in this formation is also controlled by factors such as the abundances of lime mud and nummulithoclastic debris.

Although there is no standard method of estimating permeability in carbonate rocks, a simple model like the "best-fit curve" technique is too inaccurate to predict high-quality reservoirs. This method draws a curve through measured core plug data by simple interpolation. The quality of the result between two core plugs strongly depends on the sampling distance of the plugs and the homogeneity of the rock. Thin intervals with high permeabilities will not be detected if they were not included in the core plug analyses. Possibly the largest limitation of this technique is that it can only be applied to wells where cores and plugs were taken. Another technique that is sometimes applied in carbonate settings is the so-called "field-wide layer" method. A detailed sequence-stratigraphic interpretation of the field is made, and porosity - permeability relationships are derived layer by layer. The method does deliver permeability predictions in non-cored wells but the predictive power of the derived relationship is often dubious in nature. Moreover, the sequence stratigraphic interpretation is a difficult and time consuming task.

Loucks *et al.* (1998) noted that core data is essential for the analysis of reservoir quality and that it is not possible to predict permeability from wireline logs. However, in this study, we will demonstrate that neural networks can predict permeability from wireline data successfully. We also attempt to show if there is any relationship between the measured logs, depositional fabric (Dunham class) and porosity.

Our approach to predicting reservoir quality is deterministic in nature. We aim to find subtle relationships between measured logs and core data that can be captured by a supervised neural network. The trained network is subsequently applied to predict relevant reservoir properties in sections lacking core information.

GEOLOGICAL SETTING

The Ypresian El Garia Formation is part of the Metlaoui Carbonate Group. Offshore Tunisia, it consists mainly of thick nummulitic packstones and grainstones (Fig. 1), and was deposited in a carbonate ramp environment (Loucks *et al.*, 1998; Macaulay *et al.*, 2001, Racey *et al.*, 2001). The formation forms the reservoir in the Ashtart oilfield in the Gulf of Gabes, offshore Tunisia, and in several other gas and oilfields in Tunisia and

Libya (Racey *et al.*, 2001). The main source rock in this region is the organic-rich Bou Dabbous Formation, the deep marine equivalent of the El Garia Formation (Racey *et al.*, 2001). The Compact Micrite Member forms the top seal.

The quality of the El Garia reservoir is variable. Porosity is generally moderate to high, mainly in the form of intraparticle and micro-porosity, whilst permeability is dominantly poor to fair and generally below 20 mD. The best quality reservoir is associated with some high permeability streaks, which are often difficult to detect. In such intervals, the primary interparticle porosity has either been preserved or reflects significant dolomitization resulting in high intercrystalline porosity (Loucks *et al.*, 1998). Reservoir quality depends on many factors, such as grain type and size, cementation and compaction, which make it difficult to predict.

NEURAL NETWORKS

Artificial neural networks belong to a group of mathematical algorithms which in general are inspired by the "brain metaphor", meaning that they try to emulate the internal processes of the human brain. They usually consist of many processing nodes that are connected by weights. Neural networks are used in many industries today to solve a range of problems including, (but not limited to) pattern recognition, regression analysis and data clustering. In the oil industry, neural networks are now routinely used in seismic reservoir characterization and seismic pattern analysis (Wong *et al.*, 1995; Mohaghegh, *et al.*, 1996; de Groot, 1999) and in general for solving complicated data problems.

Reservoir quality prediction in the El Garia Formation is just such a complicated problem. The high permeability zones in the reservoir are extremely difficult to detect since no apparent visible correlation exits between permeability and the measured / interpreted data. To tackle this problem, we choose to use a fully-connected Multi-Layer-Perceptron (MLP) of neural network. MLPs are the most common type of neural networks and are sometimes (mistakenly) referred to as "back-propagation" networks after the popular training algorithm used in the learning process. MLPs are supervised neural networks, i.e. they learn by example. The processing elements in MLPs are called perceptrons and are organized in layers: an input layer, (usually one) hidden layer, and an output layer. In our networks all nodes are connected to all nodes in the next layer and all connections have associated weights. During the training phase, the weights are updated such that the error in the output layer is minimized. The nodes of the networks depicted in this article are colour coded to indicate the relative importance. A red node has more weights attached, hence is more important in predicting the output, than yellow or white nodes.

Supervised learning approaches require an independent test set to stop training before overfitting occurs. "Overfitting" is the process in which the neural network loses its predictive power because it starts to memorize individual examples from the training set. The error on the training set continues to decrease with prolonged training but the error on the test set starts to increase. When working with geological data it is important to realize that geographical variations can significantly influence the training results. To avoid this potential problem, we decided to merge data from all wells to create training and test sets by random selection from the merged file.

It is important to realize that input attributes used in training a network must also be present when we apply the network. For example let us assume that density is one of the input attributes that is used to train the network. To apply this network, the density (log) must also be present. If not, the network will output an ‘undefined value’. It is also important to select relevant attributes; i.e. attributes that will contribute to the training result and that are not fully correlated with each other. This requires detailed study of the data and the derived attributes. Finally the data set may need special preparation to increase the network’s performance. One such technique is “balancing” the data, which is required when the data space is not sampled evenly. Balancing proved to be an important issue in this study and will be discussed later.

AVAILABLE DATA

Data from thirteen wells were available for the lithology, porosity and permeability analyses. Four wells had incomplete logging suites and had to be discarded, leaving nine wells for further analyses. Available wireline logs in these wells are gamma-ray, sonic, density, neutron porosity, sonic porosity and laterologs (deep and shallow). The wells had been cored over large sections of the El Garia Formation. Detailed core interpretations, including the depositional fabric, described in terms of the Dunham classification, dolomite percentage, presence of baroque dolomite, fossil percentage, debris percentage, abundance of lime mud and the types of porosity (interparticle, intraparticle, vug/ mouldic, fracture and micro-porosity) were available. Porosity and permeability were measured on core plugs. No fracture data was available for this study.

DATA ANALYSIS

The data was analyzed to establish relevant relationships between log and core data with the aim of predicting depositional texture (Dunham classification), porosity and permeability. Crossplots were used to increase our understanding of the data and to detect (linear) relationships between the parameters. We evaluated whether different correlations exist when the data is analyzed per stratigraphic group, member or sub-member. The results were used to select the input attributes for neural network training.

Supervised neural networks established whether non-linear relationships exist between the wireline and core parameters. This produced trained neural networks that predict Dunham classification, porosity or permeability. The prediction results were compared with the results from conventional methods to determine if the neural networks were significantly better in the prediction of porosity and permeability.

Dunham Classification

The Dunham classification (Dunham, 1962) is a widely used system of classifying limestones based on their depositional texture, and five classes are recognized (e.g. Tucker and Wright, 1990, p.20): mudstone, wackestone, packstone, grainstone and boundstone. These have been extended to nine, in the present study by recognizing intermediate categories (e.g. mud/wackestone) (Table 1). The presence of these rock types is not evenly distributed in our database. Packstone/grainstone, grainstone, and grain/boundstone are the dominant classes in the El Garia Formation, whilst the other types are rarely present (Fig.1).

Since the depositional fabric can only be described from core data, it would be useful to be able to predict Dunham class from wireline data to assign a Dunham value at each logged sample along the well track. Resistivity logs are often used to discriminate between different carbonate rock types and facies (Keith & Pittman, 1983; Serra, 1986). However, our crossplots for the El Garia Formation showed no relationship between any of the log types and the Dunham classification. The lack of correlation is supported by the poor training performance of the Multi-Layer-Perceptron (MLP) neural networks. Various combinations of logs (density, sonic, impedance, gamma-ray, neutron porosity, sonic porosity, deep laterolog, shallow laterolog and resistivity difference (LLD-LLS)) were used as input to predict the Dunham type, but no relationship was found. Nor did the correlation improve by using input data from a smaller stratigraphic interval rather than from the entire El Garia Formation (for example, from a single section or member), since it reduces the size of the database, causing a negative effect on the training performance.

Since the Dunham classes could not be predicted from wireline data, the initial idea to use Dunham class as a basis for estimating the reservoir quality or for predicting permeability could not be pursued.

TABLE 1 - near here
FIGURE 1 - near here

Core porosity

Porosity was measured directly from core data and is plotted as a frequency histogram in Fig. 2. The Dunham class and core plug measurements, like dolomite percentage, fossil content and abundance of lime mud, did not show any relationship with the core porosity. These results confirm the observations made by Macaulay *et al.* (2001), who stated that a limited relationship exits between the depositional fabric (i.e. Dunham class) and the reservoir quality in the El Garia Formation. It is likely that later changes in the rock texture by compaction and diagenesis have resulted in this poor correlation. From the poor training of the neural network it can be deduced that even a combination of diagenetic features is not sufficient to predict porosity.

For comparison, the neural network was also trained using wireline data instead of core data as an input. Crossplots showed that the core porosity has strong correlations with wireline data, especially with the density, sonic, neutron porosity and sonic porosity logs. A moderate relationship was found with the gamma-ray values, but no correlation appears to exist with the resistivity and induction logs.

FIGURE 2 - near here

The MLP neural networks were trained using all types of logs, including the impedance and the resistivity difference (LLD-LLS) (Fig. 3a). From the colour coded input nodes it is derived that the neutron porosity and the resistivity difference logs (coloured red), are the most important in predicting the porosity value. The weights that are attached to these input nodes are higher than to any of the other input nodes (coloured white or yellow). The normalised RMS plot (Fig. 3b) shows that during training of the neural network the (normalised) root-mean-square value of the error between the real porosity value and the predicted porosity values reduces. The lower the normalised RMS, the better the neural network is trained. The data that is used for neural network training (= red) and the data in the independent test set (= blue), follow the same trend, but the performance of the neural network is slightly better for the training dataset (RMS =0.57) than for the test data set (RMS 0.60). The scatter plot (Fig. 3c) shows the actual porosity values (X-axis) versus the predicted values for the training data (= red) and the independent test data set (= blue). Ideally the data are clustered around the diagonal line where the predicted value are the same as the actual value. The plot shows that the entire porosity range, from low to high values, is predicted well.

FIGURE 3 - near here

The trained neural network was applied to one of the wells to evaluate its predictive quality. The result is shown in Fig. 4. The blue line represents the porosity predicted by the neural network, while the core plug porosity measurements are shown in red. The correlation between the predicted porosity and the porosity measured on the cores is illustrated by the cross-plot in Fig. 5. In general, the prediction is good and the predicted porosity follows the same trend as the measured core plug data.

FIGURE 4 - near here

FIGURE 5 - near here

Core permeability

Permeability values in the El Garia Formation of the Ashtart Field range from 0 mD to several Darcies, but most permeability values lie below 10 mD (Loucks *et al.*, 1998), as illustrated in Fig. 6. Good reservoir intervals in the El Garia Formation are characterized by their preserved interparticle porosity or are dolomitized. The zones with high permeability are most often related to significant dolomitization during later diagenesis (Loucks *et al.*, 1998; Macaulay *et al.*, 2001). Permeability in these zones ranges from approximately 50 mD to several Darcies. Though the high permeability zones are very thin (a few meters) and are usually hard to detect. We investigated if the neural network approach could be applied to find these high permeability zones, using wireline and/or core data as an input to the neural network. Because of the distribution of the permeability data, logarithmic values were used in crossplots and as input for the neural networks.

FIGURE 6 - near here

Loucks *et al.* (1998) proposed that high permeabilities are associated in particular with (1) low abundance of lime mud, (2) a low abundance of nummulithoclastic debris, and echinoderm fragments, (3) moderate sorting, (4) minor precipitation of late burial cements and (5) dolomitization. An MLP neural network was trained using the Dunham classification and other core measurements to verify the validity of this proposal for the El Garia Formation. It was obvious that the dominant factor was core porosity, followed by the dolomite percentage and fossil content. The abundance of lime mud and debris are less important than suggested by Loucks *et al.*

Stronger relationships were found between the permeability values and the wireline data. Cross-plots show a good correlation between permeability and the density, sonic, neutron porosity and sonic porosity logs. A moderate relationship exists with the gamma-ray log and a poor correlation was found with the resistivity and induction logs. All logs formed input data for the MLP neural network, including impedance and the resistivity difference (LLD - LLS) logs, but the density, neutron and sonic porosity logs dominated the prediction of permeability (Fig. 7). The overall training performance, however, illustrates that the quality of the prediction is low. The normalized RMS is 0.74 for the training data and 0.8 for the independent test set (Fig. 7b). The scatter plot in Fig. 7c, shows that in particular the prediction of high and low permeability values, indicated by the two circles, was found to be difficult.

FIGURE 7 - near here

Since it was noted that core porosity correlates well with core permeability, it was added as input node to the neural network. The consequence of using core porosity is that a complete core porosity log must be present in order to be able to apply the neural network. Where core porosity does not exist, it must first be predicted. The training of the neural network should be based purely on the original measured core porosity to ensure that the prediction will not inherit errors from the porosity prediction.

The combination of wireline data and core porosity improved the training performance, and the normalised RMS of the training set decreased from 0.74 to 0.72 (Fig. 8). The scatter plot indicates that the lower permeability values are predicted better, though the high permeability values remain difficult to predict with confidence (plotted in the circle) (Fig. 8c). This was expected because only a few examples of high permeability were fed to the neural network and it was therefore incapable of making accurate predictions in this range. It was concluded that a balanced data-set was required in which an even distribution of examples exists throughout the logarithmic permeability range.

FIGURE 8 - near here

A balanced dataset was created using density, sonic, impedance, gamma-ray, neutron porosity, sonic porosity, deep and shallow laterolog, resistivity difference (LLD - LLS) logs together with the measured core porosity and permeability values from nine wells. The data set was extracted from the entire El Garia Formation and originally contained 1463 samples. Fig. 6 displays the uneven distribution of the permeability measurements, nearly 80% of which were between 0 and 20 mD, and with a peak below 10 mD (933 measurements, i.e. 64%). To create a more even distribution, the data was subdivided into twelve sets based on the logarithmic permeability values. When the original number of samples per set was higher than 50, the set was reduced to 50 by deleting lines at random. If the number of samples per set was lower than 50, the set was enlarged to approximately 50 by duplicating lines. A consequent randomized filter (+/- 2%), a so-called ‘white-noise’ filter, was applied to all duplicated log and permeability data, to avoid exactly the same examples being fed to the neural network. After balancing, the total number of examples was 619. The data set was randomly split into a training and a test set to control the training of the neural network and to avoid overtraining.

The training results using this balanced data set are given in Fig. 9. The performance of the neural network was significantly improved compared to the previously trained neural networks that use unbalanced data sets. The normalized RMS-error dropped from 0.72 to 0.53 for the training set, and from 0.70 to 0.52 for the test data (Fig.9b). The prediction improvement in the high permeability range is striking (Fig. 9c).

FIGURE 9 - near here

It was concluded that MLP neural networks can predict the permeability in the El Garia Formation successfully from a combination of wireline log data and core porosity measurements, provided that a balanced data set is used with an equal distribution of samples over the entire permeability range.

The trained neural network was applied to two wells. The permeability prediction for well Ashtart-A is good to fair and values range from 0 to 60 mD (Fig. 10a). The predicted permeability (blue curve) clearly follows the trend of the measured core plug permeabilities (red curve). The neural network picked up the thin intervals with high permeability values. In stratigraphic sections where no core plug measurements were taken, e.g. E2 to D2, the neural network detected some high permeability zones. Due to the absence of core plug data, it was not possible to check if the prediction is correct. However, the high permeability values seem realistic since they correspond to high predicted porosity values that resemble the measured porosity values from the logs.

A high permeability zone in this well at approximately 2,892m, the so-called 'drain' (Loucks *et al.*, 1998), is detected, but the predicted permeability value is much lower than the core value. It should be noted that in this well, the 'drain' is very thin and comprises only one core plug sample (700 mD). The surrounding values are below 50 mD. The interval is so thin that the logs might have missed the entire interval due to their sampling rate. Alternatively, the neural network cannot predict these extreme values, or the core measurement is unrealistic; it could be affected, for example, by laboratory conditions or core plug preparation.

The predicted result for the second well (Ashtart-B) is displayed in Fig. 10b. In both the low and high permeability range it is very close to the measured values. The majority of the data is predicted to be below 100mD, but the B3-member ('drain') stands out in particular. It has a much higher permeability, with values up to 700mD. The interval is thicker than in the previous well, and it is likely that the logs have sampled the interval better, resulting in a more accurate neural network prediction for the B2 and B3 intervals in this well.

The permeability prediction for the E2 to D2 members is less than in the other sections of this well. This could be related to the fact that less core data is available from the nine wells in this interval. The neural network was not specifically trained for these members.

From the crossplot of the predicted permeability against the core plug permeability in wells Ashtart-A and Ashtart-B for the entire El Garia Formation (Fig.

11a), and the objective interval B (Fig. 11b), it can be concluded that the prediction of permeability is accurate (correlation coefficients 0.71 and 0.87 respectively).

FIGURE 10 - near here

FIGURE 11 - near here

CONCLUSIONS

Neural networks have proven to be successful in the prediction of permeability in carbonate rocks. Although correlation with single parameters is weak, a reliable prediction can be made from the combination of wireline and core (or predicted) porosity data. To achieve a high neural network training performance, it is necessary to use a well-balanced data set that has an even distribution of samples over the entire permeability range. Since core porosity is included as an input parameter for the neural network, a porosity log must be predicted prior to the prediction of permeability. The core porosity is most closely correlated with neutron porosity and the difference between the deep and shallow resistivity logs. The entire porosity range was predicted with a high degree confidence.

The initial idea to use (predicted) Dunham classes for the prediction of permeability was discarded because the rock type could not be predicted from wireline data. As it does not correlate with porosity or permeability, it cannot be used as an indicator of reservoir quality.

The neural network method is a robust technique. Provided that enough and representative data is given to the neural network for training, then reservoir quality can be reasonably predicted in un-cored intervals located in the same geological setting as wells from which training data were derived. Thin-bedded sections with alternations of, for example, high and low permeability zones, are detected as long as they were properly logged.

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Nr.	Lithology type
1	Mudstone
2	Mud/Wackestone
3	Wackestone
4	Wacke/Packstone
5	Packstone
6	Pack/Grainstone
7	Grainstone
8	Grain/Boundstone
9	Boundstone

Table 1. Extended Dunham classification scheme used in this study.

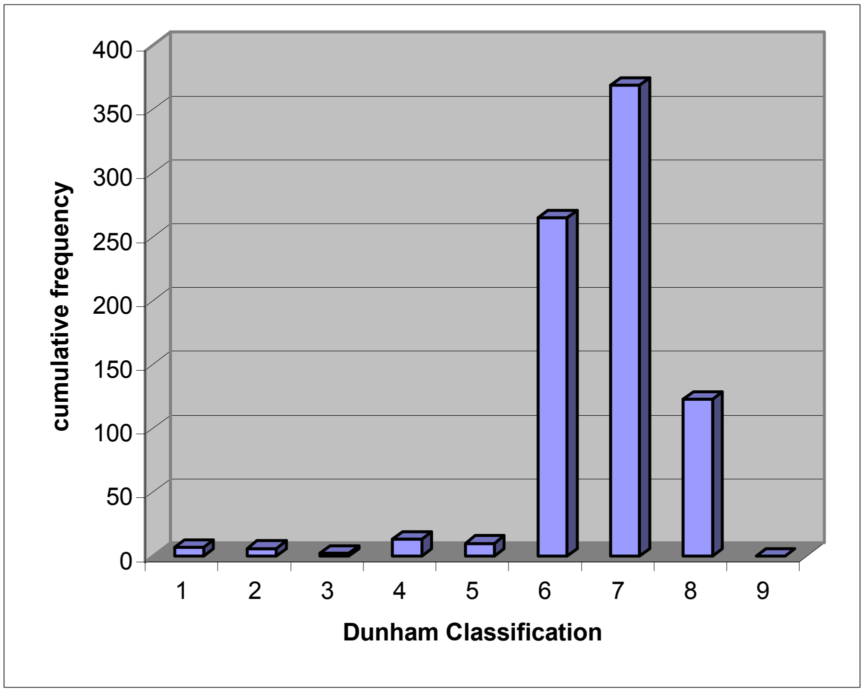


Fig. 1. Distribution of limestone textures in the El Garia Formation at the Ashtart oilfield, based on core interpretations (see Table 1 for Dunham classes).

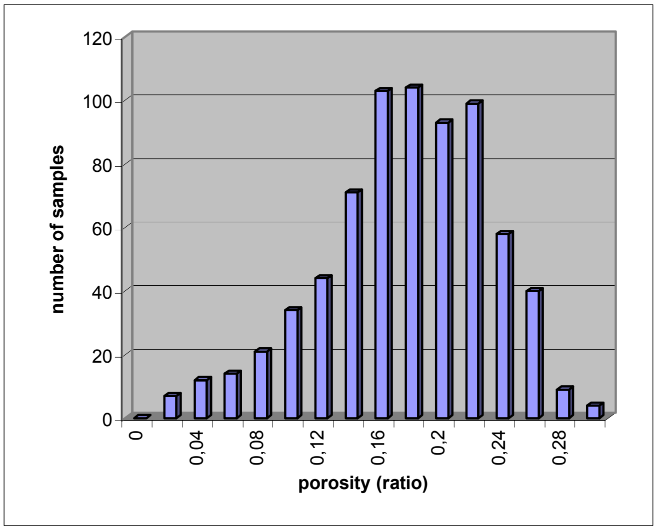


Fig. 2. Frequency distribution of porosity in the El Garia Formation, measured on core plugs.

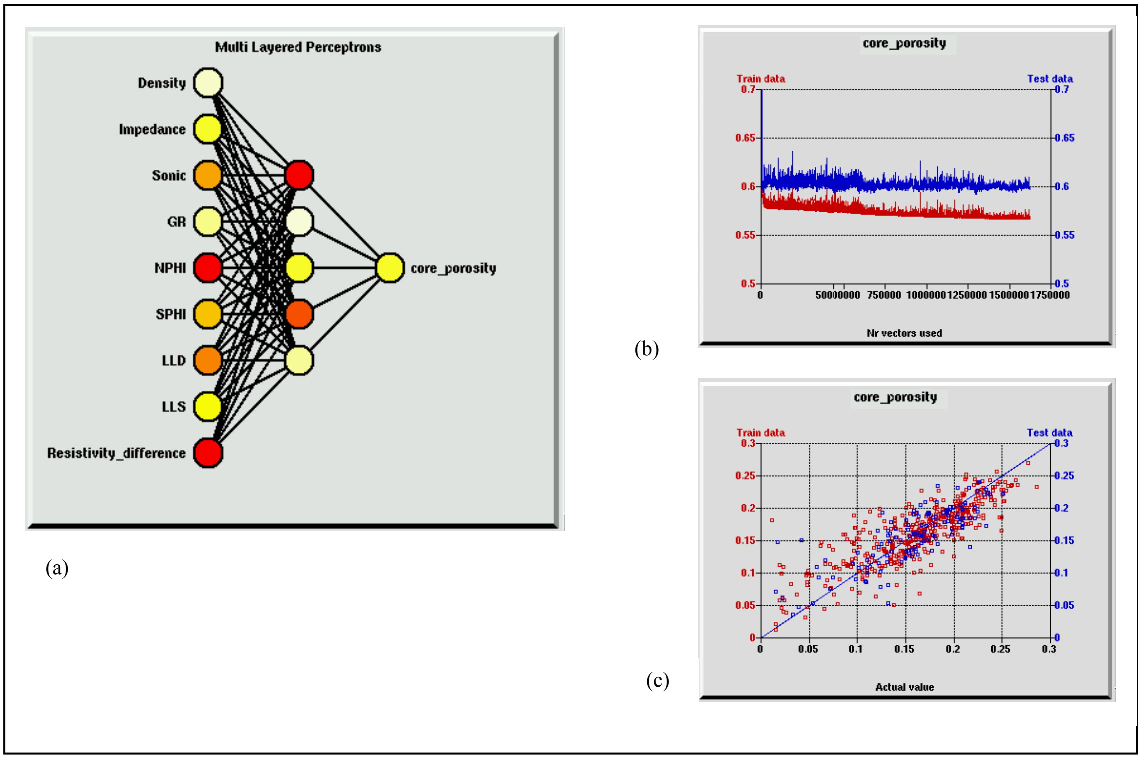


Fig. 3. Results of the neural network training to predict porosity from log data. Normalised RMS: training data 0.57 , test data 0.60 .

(a) Neural network topology (red = strong weights attached, white = low weights attached);
(b) Normalized RMS (root-mean-square) of the error between the actual porosity value and the predicted porosity (Y-axis) plotted during network training (X-axis, number of vectors) for training (red) and test data sets (blue);
(c) Scatter-plot of actual core porosity versus predicted porosity, for training data (red) and test set data (blue).

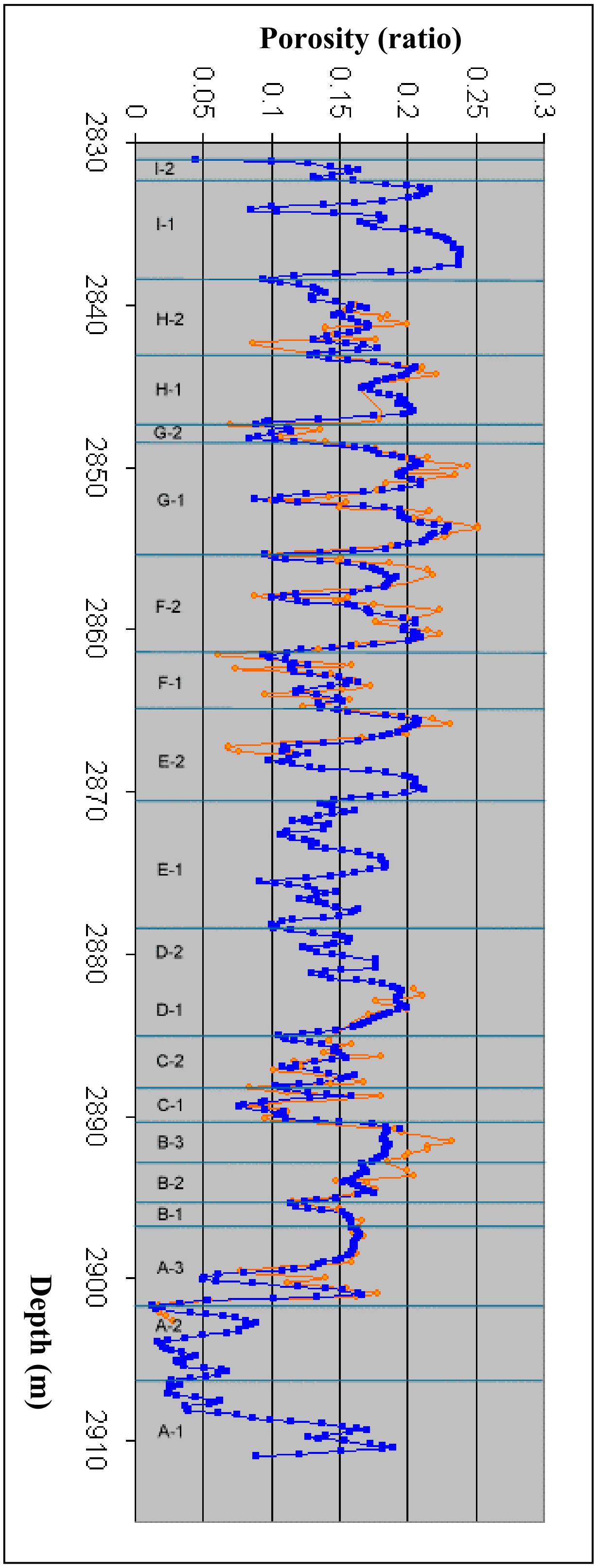
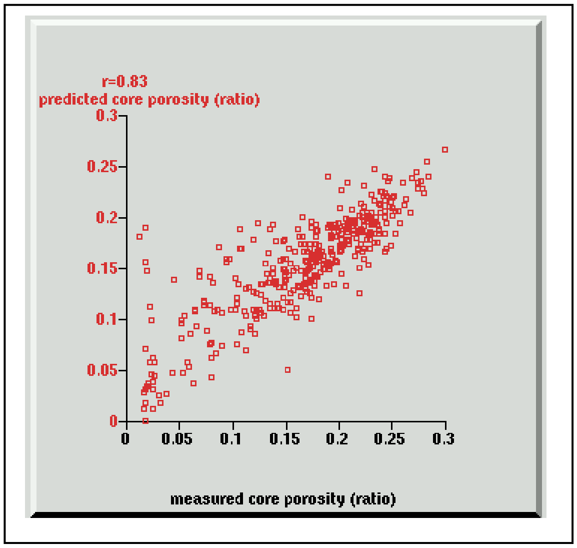


Fig. 4. Porosity prediction results on well Ashtart-A. Red dots are the porosity values measured on core plugs; blue line is the core porosity predicted by the neural network. The stratigraphic units are annotated from A-1 to I-2.



r=0.83
predicted core porosity (ratio)
0.3
0.25
0.2
0.15
0.1
0.05
0
0
0.05
0.1
0.15
0.2
0.25
0.3
measured core porosity (ratio)

Fig. 6. Frequency distribution of permeability (mD) in the El Garia Formation measured on the core plugs.

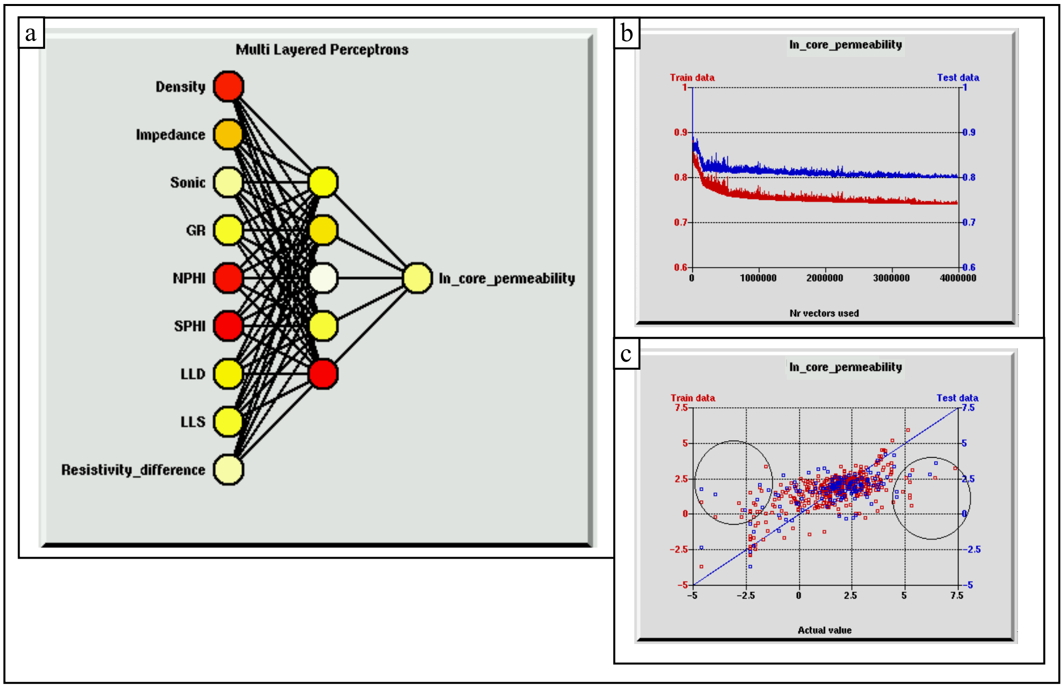


Fig. 7. Results of the neural network training to predict the logarithmic value of permeability from log data. Normalised RMS: training data 0.74, test data 0.80 .

(a) Neural network topology (red = strong weights attached, white = low weights attached);
(b) Normalized RMS (root-mean-square) of the error between the actual logarithmic permeability value and the predicted value (Y-axis) plotted during network training (X-axis, number of vectors) for training (red) and test data sets (blue);
(c) Scatter-plot of actual core permeability versus predicted permeability, for training data (red) and test set data (blue). Circles indicate data points that are predicted far too low (right circle) or too

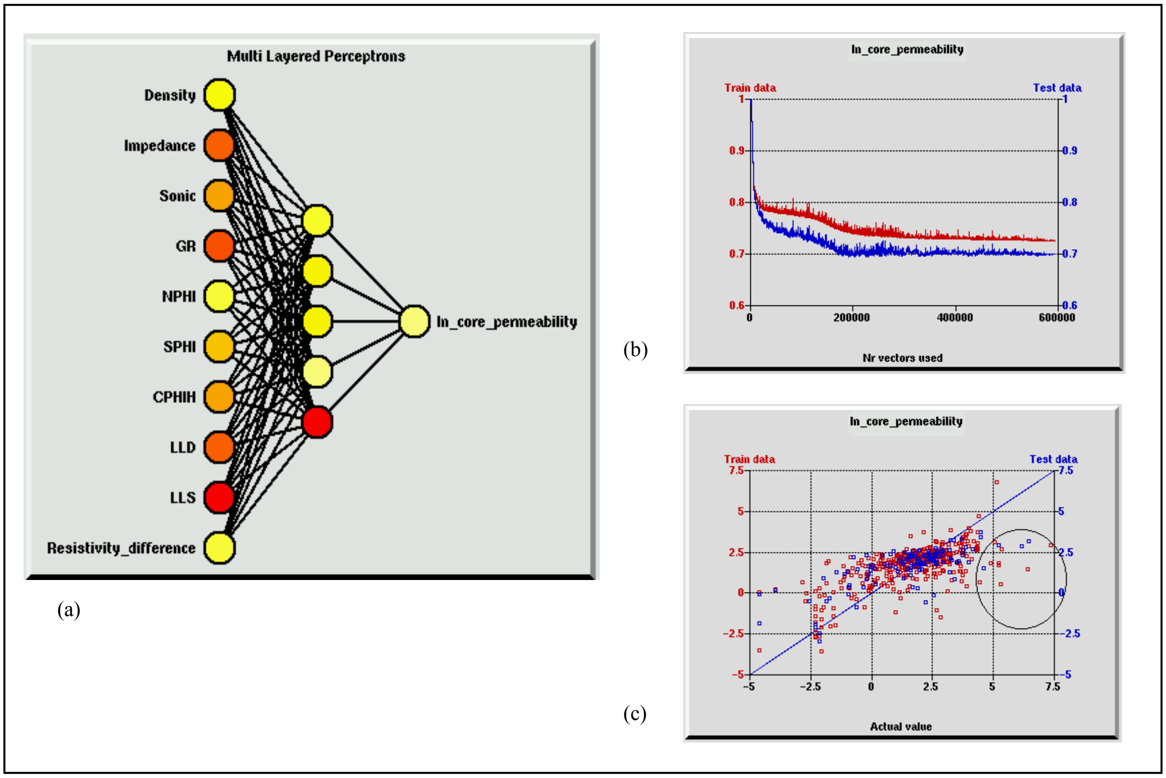


Fig. 8. Results of the neural network training to predict the logarithmic value of permeability from log data and core porosity data. Normalised RMS: training data 0.72 , test data 0.70 .

(a) Neural network topology (red = strong weights attached, white = low weights attached);
(b) Normalized RMS (root-mean-square) of the error between the actual logarithmic permeability value and the predicted value (Y-axis) plotted during network training (X-axis, number of vectors) for training (red) and test data sets (blue);
(c) Scatter-plot of actual core permeability versus predicted permeability, for training data (red) and test set data (blue). Circle indicates data points that are predicted far too low.

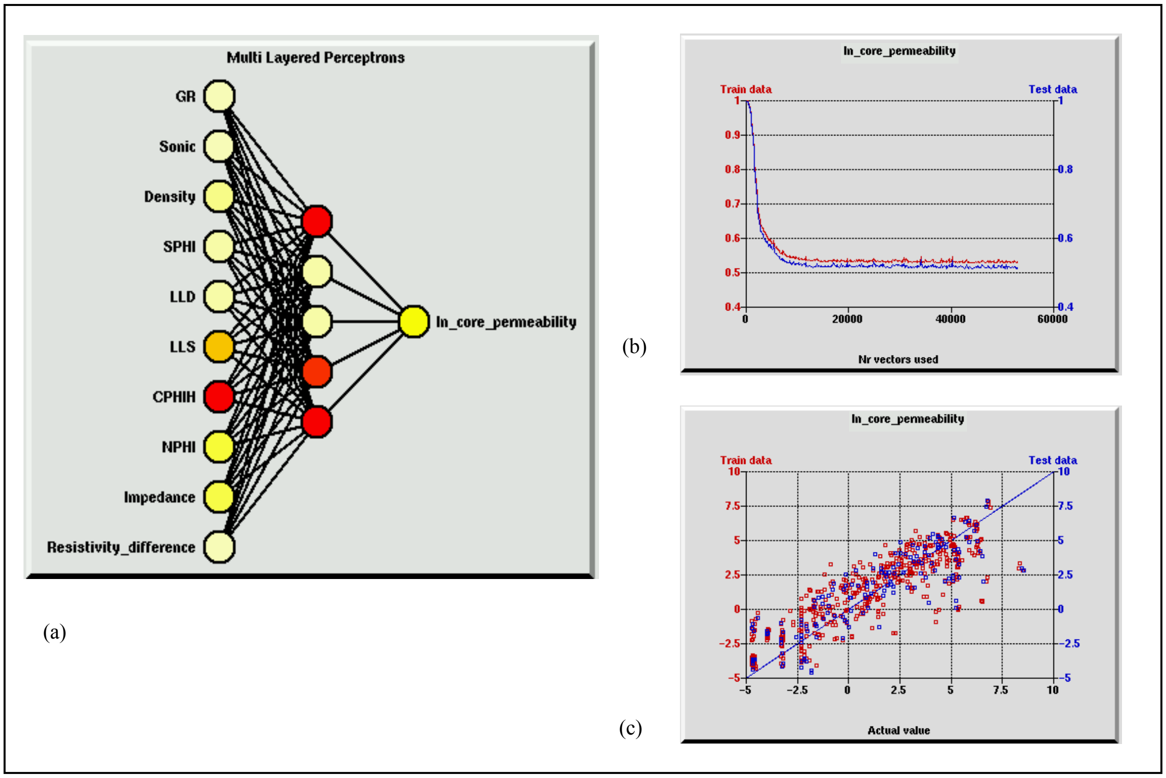


Fig. 9. Results of the neural network training to predict the logarithmic value of permeability from log data and core porosity data, using a balanced data set. Normalised RMS: training data 0.53 , test data 0.52 .

(a) Neural network topology (red = strong weights attached, white = low weights attached);
(b) Normalized RMS (root-mean-square) of the error between the actual logarithmic permeability value and the predicted value (Y-axis) plotted during network training (X-axis, number of vectors) for training (red) and test data sets (blue);
(c) Scatter-plot of actual core permeability versus predicted permeability, for training data (red) and test set data (blue).

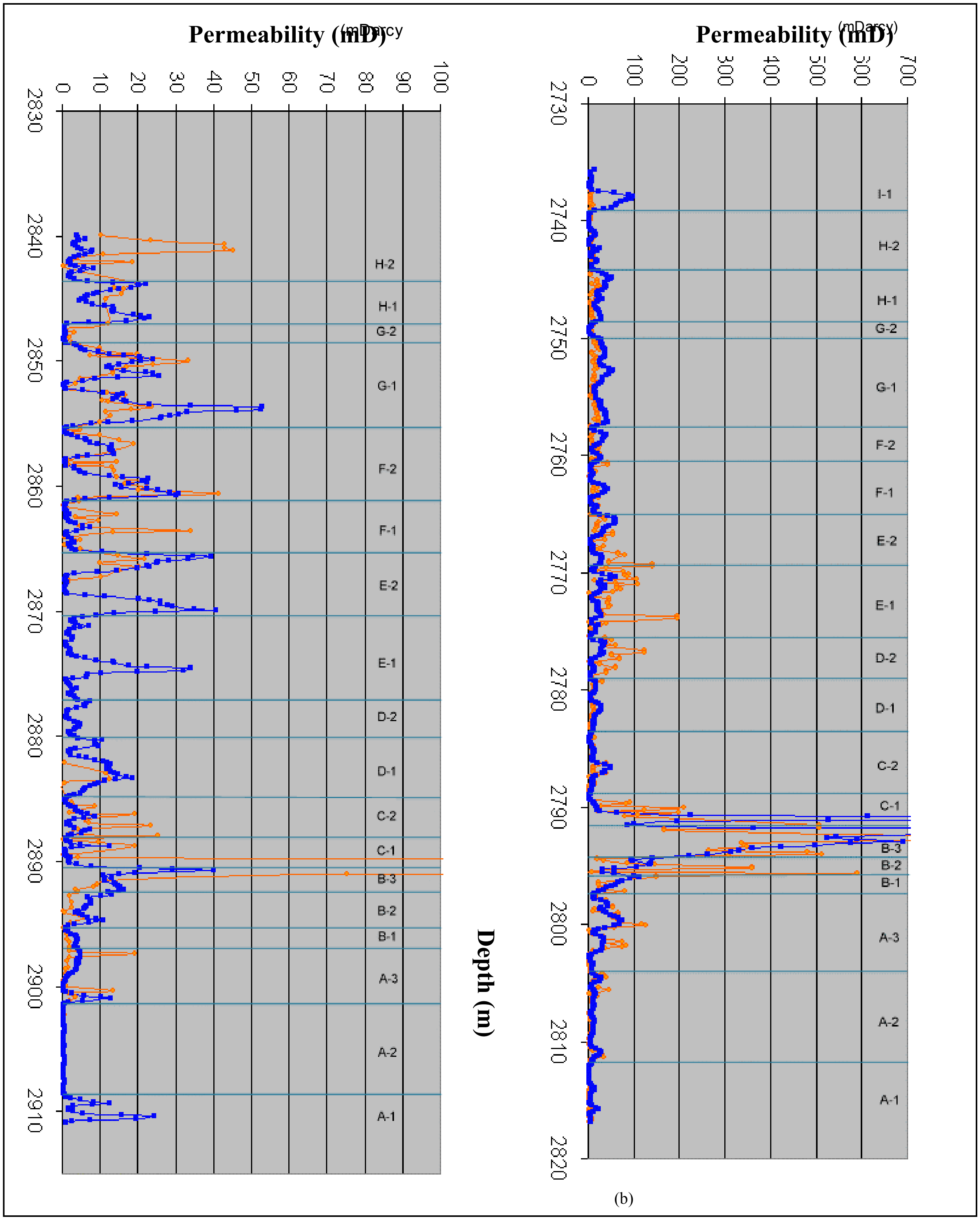


Fig. 10. Permeability prediction results. The red curves are the permeability measured on core plugs; the blue curves are the predicted core permeability by the neural network. The stratigraphic units are plotted from A-1 to I-1.

(a) Well Ashtart-A
(b) Well Ashtart-B

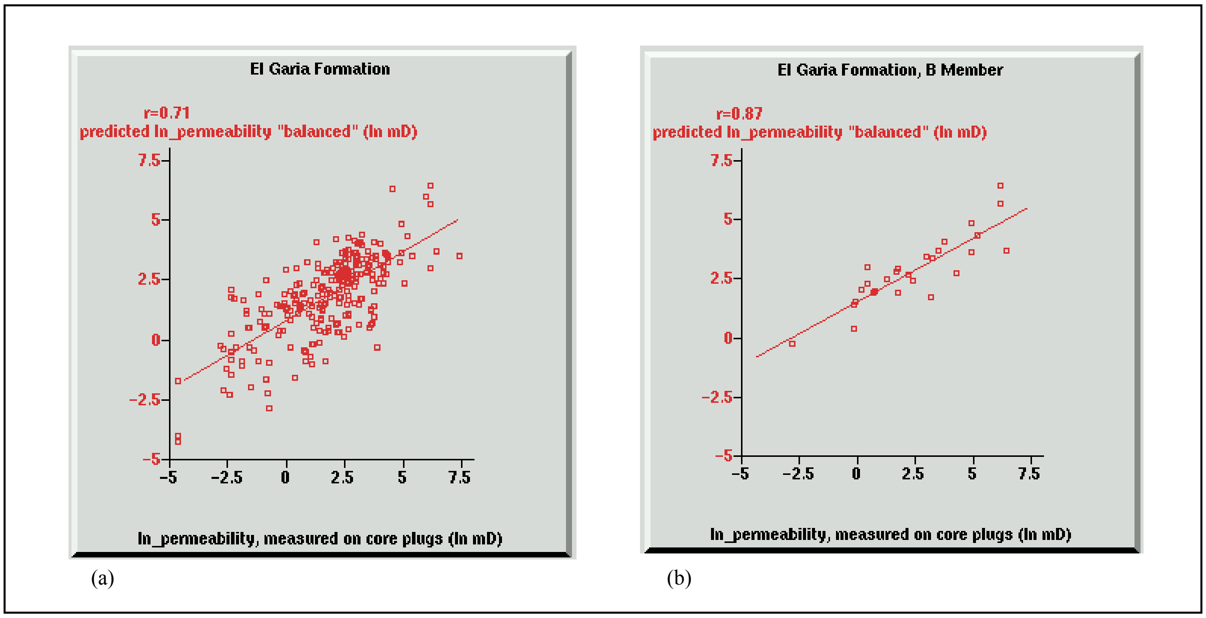


Fig. 11. Correlation between (logarithmic) permeability measured on core plugs and predicted (logarithmic) permeability.

(a) in the complete El Garia Formation (r = 0.71)
(b) in the B-member of the El Garia Formation (r = 0.87)