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# Lithofacies identification using multiple adaptive resonance theory neural networks and group decision expert system

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**Abstract**

Lithofacies identification supplies qualitative information about rocks. Lithofacies represent rock textures and are important components of hydrocarbon reservoir description. Traditional techniques of lithofacies identification from core data are costly and different geologists may provide different interpretations. In this paper, we present a low-cost intelligent system consisting of three adaptive resonance theory neural networks and a rule-based expert system to consistently and objectively identify lithofacies from well-log data. The input data are altered into different forms representing different perspectives of observation of lithofacies. Each form of input is processed by a different adaptive resonance theory neural network. Among these three adaptive resonance theory neural networks, one neural network processes the raw continuous data, another processes categorical data, and the third processes fuzzy-set data. Outputs from these three networks are then combined by the expert system using fuzzy inference to determine to which facies the input data should be assigned. Rules are prioritized to emphasize the importance of firing order. This new approach combines the learning ability of neural networks, the adaptability of fuzzy logic, and the expertise of geologists to infer facies of the rocks. This approach is applied to the Appleton Field, an oil field located in Escambia County, Alabama. The hybrid intelligence system predicts lithofacies identity from log data with 87.6% accuracy. This prediction is more accurate than those of single adaptive resonance theory networks, 79.3%, 68.0% and 66.0%, using raw, fuzzy-set, and categorical data, respectively, and by an error-backpropagation neural network, 57.3%. 

*Keywords:* Fuzzy rules; Pattern recognition; Petroleum reservoir characterization; Carbonates

## 1. Introduction

Lithofacies (rock type) identification is important for many geological and engineering disciplines (Chang, 1999). Lithofacies can be used to correlate the important characteristics of a geologic unit, such as mineralogy, depositional fabric, fossil content, or inferred origin (Rider, 1996). For petroleum reservoir characterization, the primary task is to identify lithofacies of the reservoir rocks. The purpose of this paper is to describe an automated method of predicting reservoir

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rock characteristics from commonly available well-log data.

There are generally two kinds of petroleum reservoirs: carbonate and siliciclastic. The former is composed chiefly of limestone or dolomite and the latter, sand or sandstone. However, more detailed reservoir classification is required for efficient reservoir development. Conventionally, one identifies lithofacies by direct observation of cores. Cores are costly to collect, core recovery is commonly less than one hundred percent, and cores seldom encompass the entire stratigraphic interval of interest. Also, core description can be extremely time-consuming. Therefore, a lower-cost method not requiring cores but providing similar or higher accuracy is desirable. In this paper we use well logs, which provide indirect information about the subsurface and are far less expensive. Well logs are recordings of geological properties of subsurface rock formations at depth retrieved by electrical, physical, or radioactive devices. Well-log measurements can be classified into logfacies. Logfacies are defined as the collective set of log responses, reflecting both the rock and fluid properties, allowing discrimination among beds or sedimentary units. Logfacies commonly correspond to lithofacies when they are calibrated with core descriptions. Thus, logfacies may be constructed as surrogates for lithofacies. Classifications that learn to identify logfacies can then be used to predict lithofacies in non-cored wells or non-cored intervals in cored wells.

Associating well-log data with lithofacies can be difficult due to the heterogeneous nature of rocks, especially carbonate rocks. Compared with siliciclastic lithofacies, carbonate lithofacies show subtle changes in well-log responses; thus, their identification using log data is more demanding. Also, lithofacies can be defined using any set of rock properties. However, only lithofacies defined by variations in properties that affect well-log response can be identified using well-log data. Fortunately, some useful rock properties, e.g., porosity and bulk density, affect well-log response. Well-log data are used in this paper to correlate the lithofacies.

## 2. Neural networks

Conventional computing algorithms or statistical methods have been shown inadequate for certain geological problems (Baldwin et al., 1990; Bloch, 1991; Doveton, 1994; Moline and Bahr, 1995) especially in carbonate reservoir characterization. Some researchers in geology have recently employed back propagation neural networks (BPNNs) in an attempt to improve on past performance in solving such problems (Rogers et al., 1992, 1995; Yang et al., 1996). However, BPNNs have several significant disadvantages. First, convergence during training is slow and there is no guarantee of reaching the user-defined acceptable error range. Second, the cost of retraining the networks when new information is presented can be prohibitive. Further, when test data are located outside the training data range, BPNNs cannot classify them; thus, the discriminating ability is not assured. BPNNs adequately deal with well-bounded and stable problems, because training sets may cover the entire expected input space. Unfortunately, in reservoir characterization problems, variables commonly are neither well-bounded nor stable. New lithofacies and new values of important rock properties are often encountered. This is particularly true of carbonate reservoirs like those of the Smackover Formation (from which the present example is taken), because carbonate reservoirs exhibit patchy heterogeneity at a variety of scales (e.g., Kopaska-Merkel and Mann, 1992).

Neural networks learning may be broadly grouped as supervised and unsupervised. In supervised learning, the network learns from a training set consisting of inputs and the desired outputs. Learning is accomplished by adjusting the network weights so that the difference between the desired and network computed outputs is minimized. BPNNs are examples of supervised learning. Unsupervised learning requires only input data. During the learning process, the network weights are adjusted so that similar inputs produce similar outputs. Kohonen's self-organizing maps (SOMs) and adaptive resonance theory (ART) neural networks are examples of unsupervised learning. They extract statistical regularities from the input data automatically rather than using desired outputs to guide the learning processes. Several researchers employed pattern recognition with unsupervised-learning neural networks as pattern-recognizers; e.g., SOMs and ART neural networks (Baldwin et al., 1990; Chang et al., 1998), to solve a lithofacies identification problem. There are commonly two distinct modes of operation in pattern recognition: training and production (Looney, 1996). In the training mode, recognizers are trained with training data (e.g., well-log data), and data are grouped in clusters. For this study, clusters represent logfacies. After calibrating these logfacies with the corresponding core descriptions, relationships between logfacies and lithofacies are established. In the production mode, trained recognizers recognize the logfacies from input data and determine lithofacies based on the relationships established in the training phase. In designing the recognizer, determination of the significant attributes fed to the recognizer is very important. In this study, geological experts provided lithofacies definitions and their attributes. The geologically defined lithofacies used were chosen because they are readily recognized, geologically meaningful, and differ in significant properties that affect both well-log response and reservoir quality (Kopaska-Merkel et al., 1992; Markland, 1992; Kopaska-Merkel and Hall, 1993).

We chose ART neural networks rather than SOMs as the logfacies-recognizer because the ART networks are capable of incrementally increasing the number of clusters if needed (Fausett, 1994; Bigus, 1996). This is a very important feature since the studied variables are not well-bounded as discussed previously. Hence, we propose a logfacies-recognizer system consisting of three adaptive resonance theory, ART2, neural networks, and one group-decision expert system using fuzzy if–then rules to identify lithofacies from the output logfacies.

## 3. ART2 neural networks

ART2 is a neural network algorithm derived from adaptive resonance theory (Carpenter and Grossberg, 1987). It is a clustering algorithm accepting both continuous and binary data. There are many variants of ART2; in this study, we employed the ART2 algorithm in Fausett (1994). ART2 can learn about significant new classes, yet remain stable in response to previously learned classes. This characteristic enables ART2 to meet the challenges of geological problems where unexpected natural variations are common. Slow-learning-mode ART2 s are employed to prevent category proliferation (Carpenter et al., 1995.[1]). ART2 uses a vigilance parameter supplied by domain experts (geologists and geophysicists in this context) acting here as a threshold value to filter those inputs that do not match any stored logfacies (Carpenter and Grossberg, 1987). The value of vigilance parameter ranges from 0.0 to 1.0. Varying the vigilance parameter values, dependent upon users' experience, allows the ART2 to recognize both abstract categories and specific individual categories (Kosko, 1997). When the vigilance parameter is set to 1, the input pattern must match the prototype exactly. Networks will report them with "labels" and assign stored logfacies with the closest similarity as the winners for these labeled inputs. Users should be cautious making inferences based on labeled clusters. The algorithm and network architecture of ART2 are discussed in Appendix A. Although fuzzy sets and degrees of membership concepts are used in this study, no FuzzyART algorithm is used (Kosko, 1997).

Studying a system using multiple sources (sensors) of observation can further enhance understanding of the system if these sources provide different perspectives of behaviors of the system (Benediktsson et al., 1990; Serpico and Roli, 1995; Chang, 1999). In this study, the inputs consist of depth and the following logs: density, neutron, sonic, and velocity-deviation logs. The velocity-deviation log is calculated from the sonic log and the neutron-porosity or density log. It is used to account for the effects of pore type in carbonate rocks (Anselmetti and Eberli, 1999). Combinations of these inputs compose each set of observations of logfacies. To obtain multiple observations, we artificially alter the form of inputs into raw, categorical, and fuzzy-set inputs. Raw inputs are the most commonly used and can be original (discrete-valued or continuous-valued) or transformed (e.g., logarithmic or normalized) data. Categorical data are used to emphasize the significant features in the corresponding categories rather than the actual values. In categorical data representation, a given input can be assigned to one only specific category. However, most geological data are continuous, rather than crisp values; they exhibit gradual transitions from one category to another category. To apply data to multiple categories with different degrees of membership, fuzzy sets are employed providing transitions among categories of data.

For the first ART2, all input values are normalized (i.e., to the interval [0, 1]) and there are five input nodes, $x_i$, $i = 1 \ldots 5$. There are also five input nodes, $y_i$, $i = 1 \ldots 5$ for categorical numbers in the second ART2. The nature of the boundaries between adjacent categories can be extracted from the experts' knowledge and/or training-well data. For instance, if the range of neutron log values for bind/boundstone is mostly between 18.5% and 25% then values near 18.5 and 25 are chosen as two neutron log category boundaries. Each variable is divided into consecutive numbered categories starting with 1. Number of categories of depth, neutron log, density log, sonic log, and velocity-deviation log are 7, 5, 4, 5, and 6 categories, respectively. Given a datum point $Y = (y_1, y_2, \ldots, y_5)$, if its depth belongs to category 2, neutron porosity category 4, density porosity category 1, density porosity category 3, and velocity-deviation category 6, then its input values will be $Y = (2, 4, 1, 3, 6)$.

The third ART2 consists of 34 input nodes, $z_i$, $i = 1 \ldots 34$, each corresponding to one fuzzy set. There are 11, 6, 6, 6, and 5 fuzzy sets for depth, neutron log, density log, sonic log, and velocity-deviation log, respectively. The value $z_i$ is the degree of membership with which an input datum belongs to the $i$-th fuzzy set and values range from 0 to 1.

The values of vigilance parameters of three ARTs are determined empirically considering domain experts'

[1] Distributed ART and ARTMAP architectures, http://cns-web.bu.edu/muri/year 1-report/4c.html.

knowledge. The values are 0.995, 0.995 and 0.95 for raw, categorical, and fuzzy-set ARTs respectively.

## 4. Group-decision expert system

A group-decision expert system is employed to determine the lithofacies produced from ART2 s — one processes raw continuous data, another processes categorical data, and the third processes fuzzy-set data. The outputs of these ART2 s are the logfacies to which the given inputs belong. Fuzzy if–then rules are employed because of their capability of processing linguistic variables, and uncertainty associated with outputs (Chang et al., 1997). After calibrating these logfacies with the corresponding core descriptions, the relationships between logfacies and lithofacies are established and stored. Table 1 shows these associations for outputs from all three ART2 s.

Several fuzzy rules were extracted from the training well based on the relationships among logfacies and lithofacies obtained as well as the geologic experts' knowledge about the rocks in the field. These fuzzy rules are listed below, where R-cluster, C-cluster, and F-cluster denote clusters produced from ART2 s processing raw, categorical, and fuzzy-set data respectively.

- Rule 1: IF F-cluster contains Wackestone, THEN Final-lithofacies is Wackestone.
- Rule 2: IF R-cluster contains Packstone, or C-cluster contains Packstone, or F-cluster contains Packstone, THEN Final-lithofacies is Packstone.
- Rule 3: IF rule 1 not fired, and F-cluster contains Grainstone, THEN Final-lithofacies is Grainstone.
- Rule 4: IF rules 1 and 2 not fired, and R-cluster contains Bind/Boundstone, or C-cluster contains Bind/Boundstone, or F-cluster contains Bind/Boundstone, THEN Final-lithofacies is Bind/Boundstone.
- Rule 5: IF none of the above rules fired, THEN Final-lithofacies is lithofacies with maximum counts.

Rules are fired based on the potential lithofacies obtained from R-cluster, C-cluster, and F-cluster. These rules are considered "prioritized rules." The purpose of using prioritized rules is to emphasize the importance of the firing sequence and save computation time. The priority of the rules is determined by the rule number; i.e., rule 1 is checked first, rule 2 next, etc. Additionally, at some time, the next rule in line will not be fired because the previous firings have satisfied some criteria. For example, if rule 1 is fired, and the presence of some wackestone is detected, then rule 3 and rule 4 will not be checked, because the presence of wackestone implies that grainstone and bind/boundstone are unlikely to be present. Thus, rules are not simply extracted from the training data, but also modified with knowledge acquired by geologists in the field. In inferring a rule, the degree of fulfillment of the conditions (output from ARTs with degree of certainty) is also considered to measure the likelihood that its implications are correct. If none of rules 1 to 4 fired, a counting algorithm that employs the majority-votes concept is used. The frequencies of occurrence and the degree of certainty of each occurrence from the three ART2 s are computed and aggregated. The lithofacies with the maximum aggregated value is selected. If there is a tie, all the tied lithofacies are listed, and it is inferred that multiple lithofacies coexisted or that a lithofacies with intermediate characteristics existed. Because the sampling interval is 0.3 meters, either interpretation is plausible in patchy depositional systems like that of the Smackover Formation in Alabama.

The following example illustrates the resolution of firing multiple rules. If rule 1 F-cluster is fired with Wackestone having a degree of membership of 0.5, then the confidence of final-lithofacies as Wackestone is 0.5. If rule 2 R-cluster is fired with Packstone having a degree of membership of 0.8, then the confidence of final-lithofacies as Packstone has

Table 1
Associations between logfacies and lithofacies[a]

| R-Cluster | | C-Cluster | | F-Cluster | |
|---|---|---|---|---|---|
| Logfacies | Lithofacies | Logfacies | Lithofacies | Logfacies | Lithofacies |
| 0 | W/P | 0 | W/P | 0, 10 | W/P |
| 1, 2, 6, 11 | P/G | 1, 6 | G/B | 1, 3, 7, 15, 18 | P/G |
| 3, 4, 8, 9 | G | 2 | G | 2, 4, 11, 12, 13, 14, 17 | G |
| 5, 10 | G/B | 3 | P/G | 5 | G/B |
| 7 | P | 4 | B | 6, 9 | B |
| | | 5 | P | 8, 16 | P |

[a] W, P, G and B indicate Wackestone, Packstone, Grainstone and Bind/Boundstone, respectively.

certainty factor of 0.8. The one with the highest certainty factor will be chosen as the final result; in this example, it is Packstone, certainty factor equal to 0.8, rather than Wackestone, certainty factor equal to 0.5.

To assess the reliability of the output from ART2, special attention is given to output with the "new-cluster" label. In cases in which some clusters are labeled "new-cluster", only clusters without labels are assessed. In cases in which all are labeled, all clusters will be assessed and treated equally. A special "final-new-lithofacies" tag will be attached to the final lithofacies,

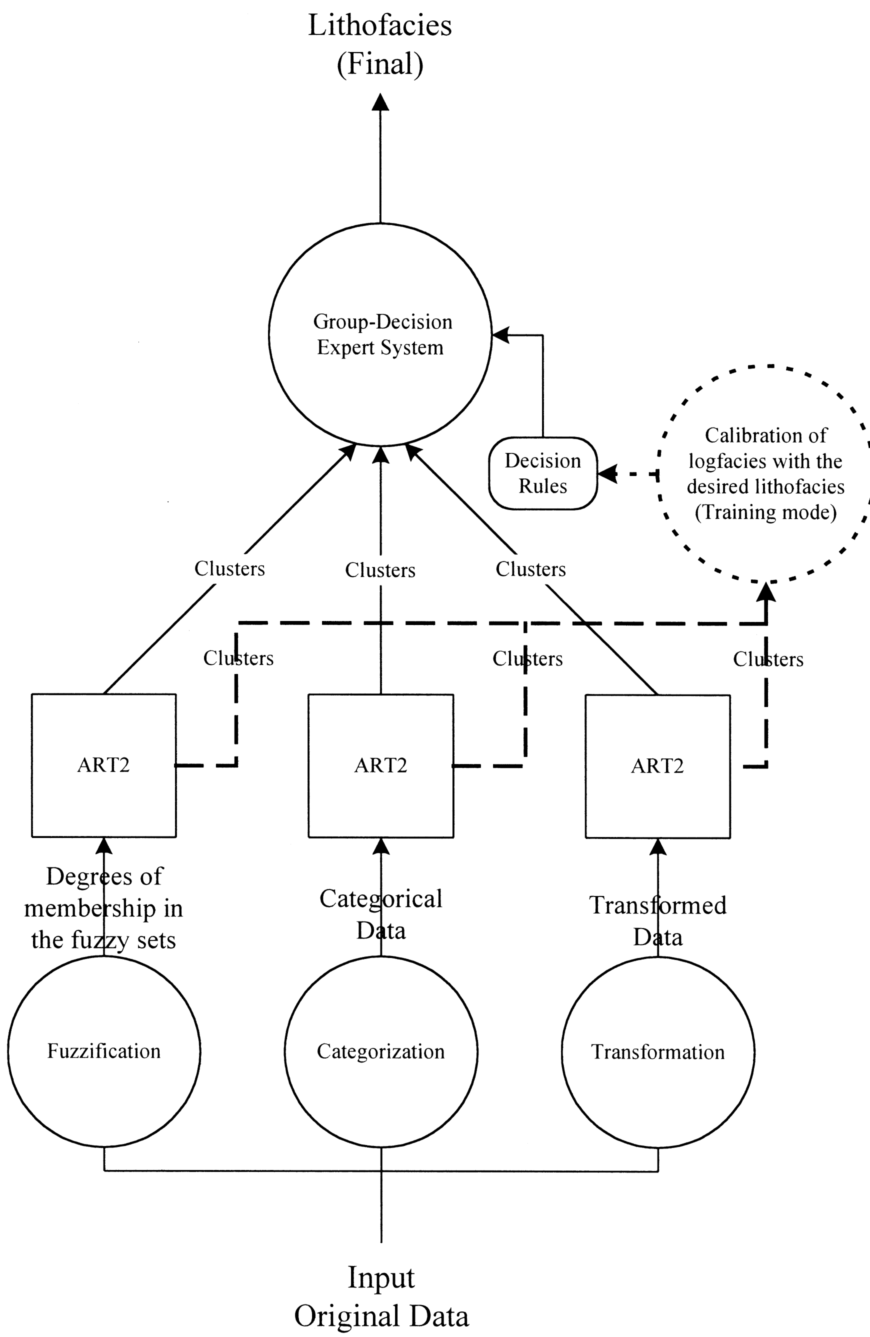


Fig. 1. System diagram for logfacies-recognizer.

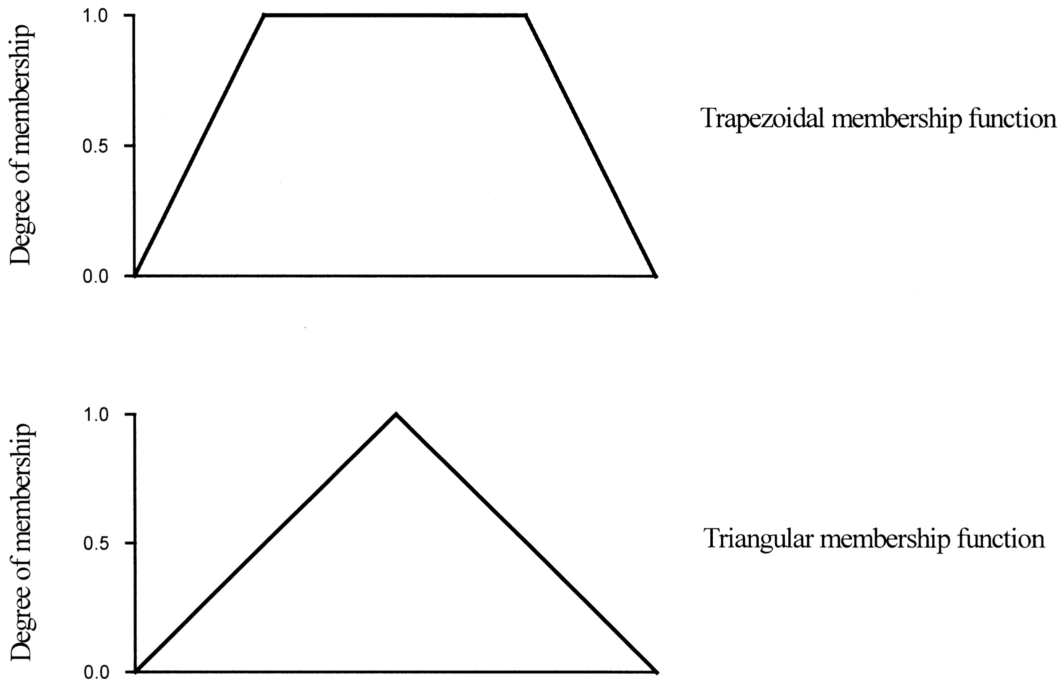


Fig. 2. Triangular and trapezoidal membership functions.

if two or three clusters from the ART2 s were labeled, indicating that the answers may be less reliable.

A system diagram employed for this paper is shown in Fig. 1. The dashed-line components in the figure process the calibration during the training mode but stay inactive during the production mode. Fuzzy sets can be determined by experts and/or experience. In order to process the input information, corresponding membership functions are used to transform the input data into fuzzy sets. These functions can be of arbitrary shapes suiting the particular needs of an application (Klir and Yuan, 1995). The triangular and trapezoidal membership functions as shown in Fig. 2 were used in this study.

## 5. Source of data

The cores and well-logs used in this paper were from wells (Alabama State Oil and Gas Board Permit ♯3986, ♯3854, ♯4633, ♯4835, and ♯6247) in Appleton Field, located in north-central Escambia County, Alabama (Markland, 1992; Kopaska-Merkel and Hall, 1993). The field produces oil from varied carbonate strata of the Smackover Formation at a subsea depth of approximately 3930 m. Cores were sampled at 0.3 m intervals, except the core from well ♯6247, which is continuous. There are 157 core data points available in the training well and 241 in the test wells.

Core examination revealed four major lithofacies in the training well (♯3986) (Dunham, 1962): wackestone, packstone, grainstone, and bind/boundstone. Mudstone is not found in the training well but appears in test well ♯6247. The input data are composed of: (1) depth, (2) neutron porosity, (3) density porosity, (4) interval velocity, and (5) velocity-deviation.

The logfacies-recognizer was trained on the data from well ♯3986 and then tested on wells ♯3854, ♯4633, ♯4835, and ♯6247. A geologist described cores from all five wells and identified lithofacies without knowing the recognizers' output. Subsequently, cores from test wells were classified using the lithofacies defined for the training well by the recognizer.

## 6. Results and discussion

The geologist's core description and recognizer's prediction are compared in Fig. 3. Discrepancies occur in sporadic zones most of which are only 0.3 m thick. Isolated 0.3 m intervals probably are too small to affect hydrocarbon production and therefore their misidentification is of no practical significance. This is because in carbonate rock units like the Smackover thin units generally do not retain consistent character-

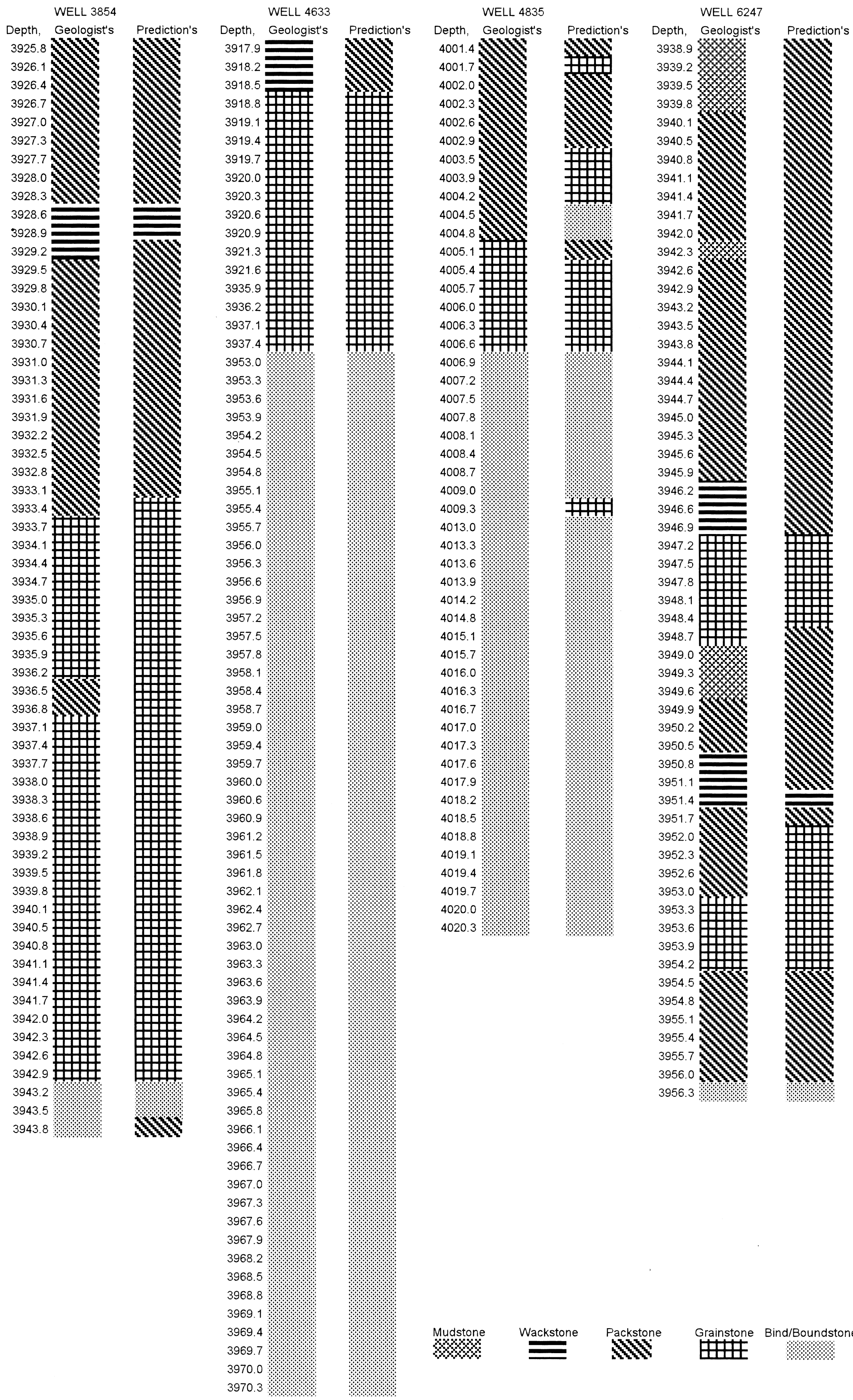


Fig. 3. Comparisons between geologist's description and predictions.

Table 2
Statistics of predictions of lithofacies in test wells

| Well number | Number of available data points | Number of match data points | Match (%) |
|---|---|---|---|
| 3854 | 60 | 55 | 91.7 |
| 4633 | 74 | 71 | 95.9 |
| 4835 | 49 | 45 | 91.8 |
| 6247 | 58 | 30[a] | 51.7 |
| Total | 241 | 211 | 87.6 |

[a] Eight points of Mudstone, not seen in the training well ♯3986.

istics over distances on the order of the width of Appleton Field (about 2.8 km) (University of Alabama, 1991; Markland, 1992; Kopaska-Merkel and Mann, 1992).

The amount and quality of core and well-log data available for this study permitted appropriate tests of the networks' capability to identify lithofacies from well-log data. Table 2 lists the final results of prediction of lithofacies for test wells. Of 241 0.3 m cored intervals in the test wells, 211 (87.6%) were correctly predicted by the recognizer. Compared with the 79.3% accuracy for the raw-data ART2, 68.0% accuracy for the fuzzy-set-data ART2, 66.0% accuracy for the categorical-data ART2, and 57.3% for the BPNN, the recognizer has shown promising success. The statistics of prediction of these neural networks are listed in Table 3. Because most oil and gas production wells are either not cored or only partially cored through reservoir intervals, the successful prediction of lithofacies by the recognizer system is of considerable value. Three dimensional reservoir simulation models are commonly constructed to predict oil and gas production from fields. The output from the recognizer system will enhance the completeness and accuracy of input data available to construct such simulation models at a very modest cost.

Mudstone is not found in well ♯3986 (training well) and is tagged "final-new-lithofacies" by the system. In addition, if the system is forced to find a "best match" for mudstone, mudstone samples are classified as impermeable packstone or wackestone, which are similar to mudstone in both origin and physical characteristics. It is also noted that among 30 mis-classified data points, 22 were tagged with "final-new-lithofacies." Namely, the system did provide a "warning" for most of these mis-classifications. Due to natural variations among wells, a total of 40 points were tagged "final-new-lithofacies." In other words, for 18 of the 40 points tagged "final-new-lithofacies", the "best match" classification was judged to be correct. The system is directed to make the best choices and reports the assigned lithofacies with a "final-new-lithofacies" tag. Among these 40 points, the well ♯6247 has the maximum count (15 points; 37.5%) of "final-new-cluster" tags. This well may have significantly different subsurface physical properties from the training well (♯3986). This inferred difference is supported by the observation that well ♯3986 is a production well whereas well ♯6247 is dry.

## 7. Conclusion

We have introduced an intelligent system which is a hybrid of neural networks, fuzzy logic, and an expert system. This system has the following advantages over the traditional approaches. First, the recognizer system effectively identifies lithofacies using well-log data. Lithofacies may be identified automatically and objectively using this system. Second, the system may be more accurate than the pure neural network approach where geological variation is complex, and the expert knowledge of geologists is needed to be utilized. Third, final lithofacies identifications made by group-decisions using all ART2 s are more accurate than those made by BPNNs or a single ART2. This is demonstrated

Table 3
Number of match data points from different ARTs and group-decision system in test wells

| Well number | BPNN | Raw-data ART | Categorical-data ART | Fuzzy-set-data ART | Group-decision system |
|---|---|---|---|---|---|
| 3854 | 22 | 48 | 48 | 42 | 55 |
| 4633 | 65 | 69 | 71 | 68 | 71 |
| 4835 | 36 | 41 | 44 | 27 | 45 |
| 6247 | 15 | 33 | 17 | 27 | 30 |

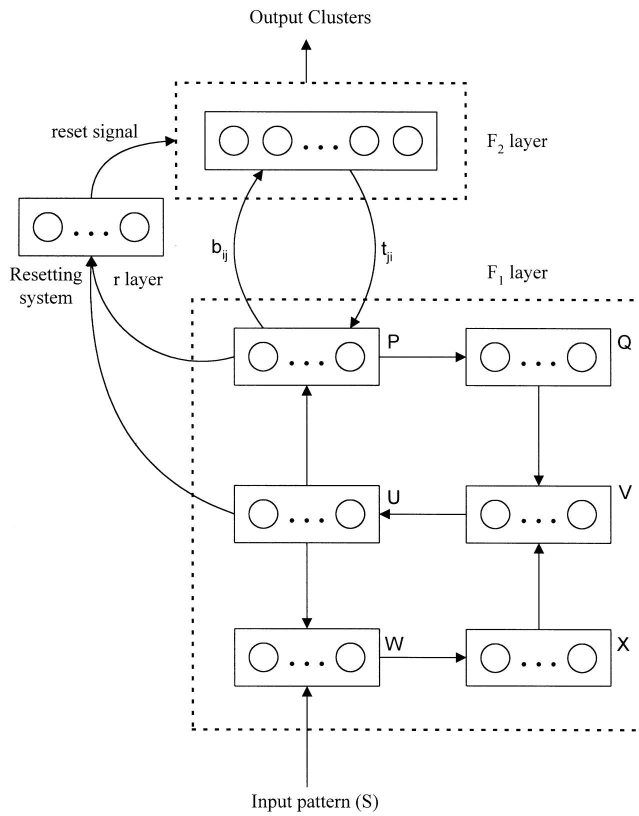


Fig. 4. Architecture of ART2.

with a real-world example. Finally, this intelligent system may be tuned to yield different degrees of details.

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## Appendix A. ART2 — architecture and learning algorithm

The basic architecture of the ART2 neural network is shown in Fig. 4. The network consists of two major layers ($F_1$ and $F_2$) and one resetting system. $F_1$ and $F_2$ layers are fully connected with the bottom-up weights ($b_{ij}$) from $F_1$ to $F_2$, and the top-down weights ($t_{ji}$) from $F_2$ to $F_1$. The $F_1$ layer includes a combination of six sublayers called W, X, V, U, Q, and P. W receives signals from input data (or called input signals, S). X normalizes signals and V performs noise suppression. After noise suppression, the given signals will be normalized again in U sublayer. P sends normalized signals to the $F_2$ layer via $b_{ij}$s and receives signals from $F_2$ layer via $t_{ji}$s. Q normalized the sums of the signals at P for the resetting condition. If a reset condition is indicated, a reset signal will be sent to $F_2$ to mark the current active node as ineligible for competition and operation of current input data will be stopped. A new set of input pattern will then be input to the W. If there is no reset and iteration count is 1, then the normalized signals at P are sent to the $F_2$ layer. If there is no reset and iteration count is greater than one, then the input pattern is accepted and top-down and bottom-up weights will be updated, as resonance has been established. The $F_2$ layer determines the clusters where the input patterns should be placed. The resetting system provides control over the degree of similarity of various criteria used. (Freeman and Skapura, 1991; Fausett, 1994; Yang, 1996; Chang, 1999)

The ART2 algorithm is summarized as follows:

1. At the beginning of a learning trial, all activations are set to zero.
2. The learning starts with one presentation of one input pattern (called S) at one time.
3. The input patterns are sent to the $F_1$ layer for normalization in sublayer X and noise suppression in sublayer V.
4. The signals from sublayer V continue to be sent to units in sublayer U for normalization again.
5. Next, signals from U are sent to its associate units in W and P sublayers.
6. Unit in W sums the signals it receives from U and S, and feeds the sum to sublayer X for normalization.
7. Unit in P sums the signals from U and from the $F_2$ layer, and sends the summed signals to Q for normalization.
8. Signals at P are sent to the $F_2$ layer through bottom-up connections by:

   $$\mathrm{yj} = \mathrm{b}_{ij}^{*}\mathrm{Pi} \text{ for all j in } \mathrm{F}_2$$

9. Now, a winner-take-all competition chooses the candidate unit (called YJ) to learn the input pattern S; YJ = max(Yj).
10. If the candidate unit is a new one, the input S will be accepted as the exemplar in the cluster, and the updating procedure will be invoked next.
11. If the candidate unit already has a stored exemplar, say Z, signals of Z is then transformed through top-down connections from $F_2$ to sublayer P of $F_1$.
12. Now, the reset mechanism checks the similarity between S and Z. The level of similarity required is dependent on vigilance parameter $\rho$,– with $0 \le \rho \le 1$. If $\rho$ is large the similarity condition becomes very stringent, so many finely divided clusters are formed. In addition to similarity checks, other user imposed constraints will also be checked.
13. After all the conditions for reset mechanism have been checked, the candidate unit YJ either will be accepted or rejected.
14. If YJ is accepted, then weights $b_{ij}$ and $t_{ji}$ will be updated next.
15. If YJ is rejected, a reset signal is sent to $F_2$. If YJ is inhibited, another uninhibited unit of $F_2$ is selected, and a new cycle of pattern matching begins (steps 9–15).
16. If there are no such uninhibited units left, a new unit is formed, and S becomes the exemplar of that cluster. The network next learns S by updating weights with equations in step 17.
17. The network updates weights for the candidate unit YJ:

    $$\mathrm{t}_{ji} = \alpha d\mathrm{ui} + \{1 + \alpha d(d-1)\}\mathrm{t}_{ji}$$

    $$\mathrm{b}_{ij} = \alpha d\mathrm{ui} + \{1 + \alpha d(d-1)\}\mathrm{b}_{ji} \text{ for all } i$$

    where $\alpha$ is learning rate and $d$ is the activation of winning $F_2$ unit.
18. The procedure described above (steps 1–17) completes a learning trial
19. Repeat steps 1–17 for all input patterns.
20. Repeat steps 1–19 a great many times for ART2 net to stabilize.

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