THE ROLE OF SOFT COMPUTING TECHNIQUES AND GEOSCIENCES FOR INTELLIGENT RESERVOIR CHARACTERIZATION AND OIL EXPLORATION

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The Role of Soft Computing Techniques and Geosciences for Intelligent Reservoir Characterization and Oil Exploration

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Abstract: As our problems become too complex to rely only on one discipline and as we find ourselves at the midst of information explosion multi-disciplinary analysis methods and data mining approaches in the petroleum industry become more of a necessity than professional curiosity. To tackle difficult problems ahead of us, we need to bring down the walls we have built around traditional disciplines such as petroleum engineering, geology, geophysics and geochemistry, and embark on true muti-disciplinary solutions. Our data, methodologies and workflow will have to cut across different disciplines. As a result, today's "integration" which is based on integration of results will have to give way to a new form of integration, that is, discipline integration. In addition, to solve our complex problems we need to go beyond standard mathematical techniques. Instead, we need to complement the conventional analysis methods with a number of emerging methodologies and soft computing techniques such as Expert Systems, Artificial Intelligence, Neural Network, Fuzzy Logic, Genetic Algorithm, Probabilistic Reasoning, and Parallel Processing techniques. Soft computing differs from conventional (hard) computing in that, unlike hard computing, it is tolerant of imprecision, uncertainty, and partial truth. Soft Computing is also tractable, robust, efficient and inexpensive. In this overview paper, we highlight role of Soft Computing techniques for intelligent reservoir characterization and exploration, seismic data processing and characterization, well logging, reservoir mapping and engineering. Reservoir characterization plays a crucial role in modern reservoir management. It helps to make sound reservoir decisions and improves the asset value of the oil and gas companies. It maximizes integration of multi-disciplinary data and knowledge and improves the reliability of the reservoir predictions. The ultimate product is a reservoir model with realistic tolerance for imprecision and uncertainty. Soft computing aims to exploit such a tolerance for solving practical problems. In reservoir characterization, these intelligent techniques can be used

for uncertainty analysis, risk assessment, data fusion and data mining which are applicable to feature extraction from seismic attributes, well logging, reservoir mapping and engineering. The main goal is to integrate soft data such as geological data with hard data such as 3D seismic and production data to build a reservoir and stratigraphic model. While some individual methodologies (esp. neurocomputing) have gained much popularity during the past few years, the true benefit of soft computing lies on the integration of its constituent methodologies rather than use in isolation.

Future research should focus on the integration of data and disciplinary knowledge for improving our understanding of reservoir data and reducing our prediction uncertainty.

1 Introduction

Last decade has witnessed significant advances in transforming geosciences and well data into drillable prospects, generating accurate structural models and creating reservoir models with associated properties. This has been made possible through improvements in data integration, quantification of uncertainties, effective use of geophysical modeling for better describing the relationship between input data and reservoir properties, and use of unconventional statistical methods. Soft computing techniques such as neural networks and fuzzy logic and their appropriate usage in many geophysical and geological problems has played a key role in the progress made in recent years. However there is a consensus of opinion that we have only begun the scratch the surface in realizing full benefits of soft computing technology. Many challenges remain when we are facing with characterization of reservoirs with substantial heterogeneity and fracturing, exploring in the areas with thin-bedded stacked reservoirs and regions with poor data quality or limited well control and seismic coverage and quantifying uncertainty and confidence interval of the estimates. Among the inherent problems we need to overcome are: inadequate and uneven well data sampling, non-uniqueness in cause and effect in subsurface properties versus geosciences data response, different scales of seismic, log and core data and finally how to handle changes in the reservoir as the characterization is in progress.

This paper reviews the recent geosciences applications of soft computing (SC) with special emphasis on exploration. The role of soft computing as an effective method of data fusion will be highlighted. SC is consortium of computing methodologies (Fuzzy Logic (GL), Neuro-Computing (NC), Genetic Computing (GC), and Probabilistic Reasoning (PR) including; Genetic Algorithms (GA), Chaotic Systems (CS), Belief Networks (BN), Learning Theory (LT)) which collectively provide a foundation for the Conception, Design and Deployment of Intelligent Systems. The role model for Soft Computing is the Human Mind. Unlike the conventional or hard computing, it is tolerant of imprecision, uncertainty and partial truth. It is also tractable, robust, efficient and inexpensive. Among main components of soft computing, the artificial neural networks, fuzzy logic and the genetic algorithms in the "exploration domain" will be examined. Specifically, the earth exploration applications of SC in various aspects will be discussed. We outlines the unique roles of the three major methodologies of soft computing – neurocomputing, fuzzy logic and evolutionary computing. We will summarize a number of relevant and documented reservoir characterization applications. We will also provide a list of recommendations for the future use of soft computing. This includes the hybrid of various methodologies (e.g. neural-fuzzy or neuro-fuzzy, neural-genetic, fuzzy-genetic and neural-fuzzy-genetic) and the latest tool of "computing with words" (CW) (Zadeh 1996). CW provides a completely new insight into computing with imprecise, qualitative and linguistic phrases and is a potential tool for geological modeling which is based on words rather than exact numbers.

These applications are divided into two broad categories. One has to do with improving the efficiency in various tasks that are necessary for the processing and manipulation and fusion of different types of data used in exploration. Among these applications are: first arrival picking, noise elimination, structural mapping, horizon picking, event tracking and integration of data from different sources. The other application area is pattern recognition, identification and prediction of different rock properties under the surface. This is usually accomplished by training the system from known rock properties using a number of attributes derived from the properly fused input data (e.g., 2D and 3D seismic, gravity, well log and core data, ground penetrating radar and synthetic aperture radar and other types remote sensing data). Then a similarity measure with certain threshold level is used to determine the properties where no direct measurement is available.

2 The Role of Soft Computing Techniques for Intelligent Reservoir Characterization and Exploration

Soft computing is bound to play a key role in the earth sciences. This is in part due to subject nature of the rules governing many physical phenomena in the earth sciences. The uncertainty associated with the data, the immense size of the data to deal with and the diversity of the data type and the associated scales are important factors to rely on unconventional mathematical tools such as soft computing. Many of these issues are addressed in a recent books, Nikravesh et al. (2002), Wong et al (2001), recent special issues, Nikravesh et al. (2001a and 2001b) and Wong and Nikravesh (2001) and other publications such as Zadeh (1994), Zadeh and Aminzadeh (1995), and Aminzadeh and Jamshidi (1994).

Recent applications of soft computing techniques have already begun to enhance our ability in discovering new reserves and assist in improved reservoir management and production optimization. This technology has also been proven useful in production from low permeability and fractured reservoirs such as fractured shale, fractured tight gas reservoirs and reservoirs in deep water or below salt which contain major portions of future oil and gas resources. Through new technology and data acquisition to processing and interpretation the rate of success in exploration has risen to 40 percent in 1990 from 30 percent in the 1980s. In some major oil companies the overall, gas and oil well drilling success rates have risen to an average of 47 percent in 1996 from 3-30 percent in the early 1990s (SOURCE OF THIS DATA?). For example, in US only, by year 2010, these innovative techniques are expected to contribute over 2 trillion cubic feet (Tcf)/year of additional gas production and 100 million barrels per year of additional oil. This cumulative will be over 30 Tcf of gas reserves and 1.2 billion barrels in oil reserve and will add over $8 billion to revenue in 2010.

Intelligent techniques such as neural computing, fuzzy reasoning, and evolutionary computing for data analysis and interpretation are an increasingly powerful tool for making breakthroughs in the science and engineering fields by transforming the data into information and information into knowledge.

In the oil and gas industry, these intelligent techniques can be used for uncertainty analysis, risk assessment, data fusion and mining, data analysis and interpretation, and knowledge discovery, from diverse data such as 3-D seismic, geological data, well log, and production data. It is important to mention that during 1997, the US industry spent over $3 billion on seismic acquisition, processing and interpretation. In addition, these techniques can be a key to cost effectively locating and producing our remaining oil and gas reserves. Techniques can be used as a tool for:

1) Lowering Exploration Risk
2) Reducing Exploration and Production cost
3) Improving recovery through more efficient production
4) Extending the life of producing wells.

In what follows we will address data processing / fusion / mining, first. Then, we will discuss interpretation, pattern recognition and intelligent data analysis.

2.1 Mining and Fusion of Data

In the past, classical data processing tools and physical models solved many real-world problems. However, with the advances in information processing we are able to further extend the boundaries and complexities of the problems we tackle. This is necessitated by the fact that, increasingly, we are faced with multitude of challenges: On the one hand we are confronted with more unpredictable and complex real-world, imprecise, chaotic, multi-dimensional and multi-domain problems with many interconnected parameters in situations where small variability in parameters can change the solution completely. On the other hand, we are faced with profusion and complexity of computer-generated data. Making sense of large amounts of imprecise and chaotic data, very common in earth sciences applications, is beyond the scope of human ability and understanding. What this implies is that the classical data processing tools and physical models that have addressed many problems in the past may not be sufficient to deal effectively with present and future needs.

In recent years in the oil industry we have witnessed massive explosion in the data volume we have to deal with. As outlined at, Aminzadeh, 1996, this is caused by increased sampling rate, larger offset and longer record acquisition, multi-component surveys, 4-D seismic and, most recently, the possibility of continuous recording in "instrumented oil fields". Thus we need efficient techniques to process such large data volumes. Automated techniques to refine the data (trace editing and filtering), selecting the desired event types (first break picking) or automated interpretation (horizon tracking) are needed for large data volumes. Fuzzy logic and neural networks have been proven to be effective tools for such applications. To make use of large volumes of the field data and multitude of associated data volumes (e.g. different attribute volumes or partial stack or angle gathers), effective data compression methods will be of increasing significance, both for fast data transmission efficient processing, analysis and visualization and economical data storage. Most likely, the biggest impact of advances in data compression techniques will be realized when geoscientists have the ability to fully process and analyze data in the compressed domain. This will make it possible to carry out computer-intensive processing of large volumes of data in a fraction of the time, resulting in tremendous cost reductions. Data mining is another alternative that helps identify the most information rich part of the large volumes of data. Again in many recent reports, it has been demonstrated that neural networks and fuzzy logic, in combination of some of the more conventional methods such as eigenvalue or principal component analysis are very useful.

Figure 1 shows the relationship between Intelligent Technology and Data Fusion/Data Mining. **Tables 1** and **2** show the list of the Data Fusion and Data Mining techniques. **Figure 2** and **Table 3** show the Reservoir Data Mining and Reservoir Data Fusion concepts and techniques. **Table 4** shows the comparison between Geostatistical and Intelligent techniques. In sections II through VIII, we will highlight some of the recent applications of these methods in various earth sciences disciplines.

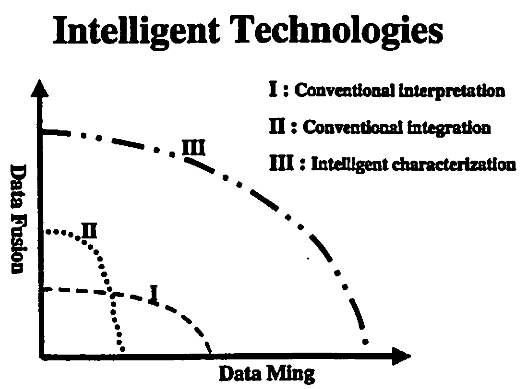


Figure 1. Intelligent Technology

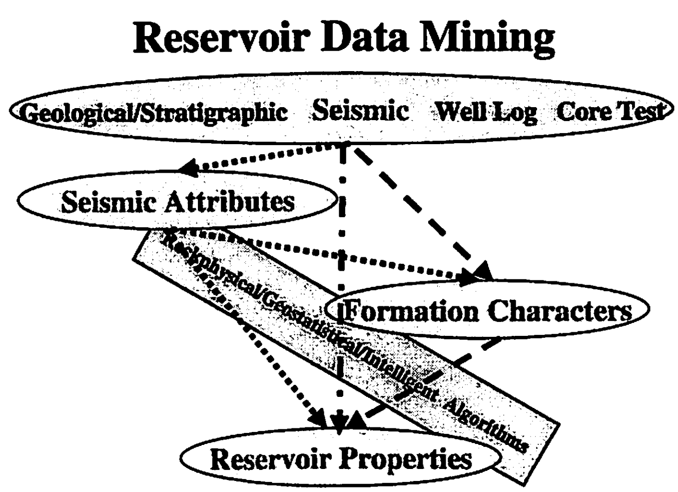


Figure 2. Reservoir Data Mining

Table 1.

Data Mining Techniques

- **Deductive Database Client**
- **Inductive Learning**
- **Clustering**
- **Case-based Reasoning**
- **Visualization**
- **Statistical Package**

Table 2.

Data Fusion Techniques

- **Deterministic**
  - **Transform based** ***(projections,...)***
  - **Functional evaluation based** ***(vector quantization, ...)***
  - **Correlation based** ***(pattern match, if/then productions)***
  - **Optimization based** ***(gradient-based, feedback, LDP, ...)***
- **Non-deterministic**
  - **Hypothesis testing** ***(classification, ...)***
  - **Statistical estimation** ***(Maximum likelihood, ...)***
  - **Discrimination function** ***(linear aggregation, ...)***
  - **Neural network** ***(supervised learning, clustering, ...)***
  - **Fuzzy Logic** ***(Fuzzy c-Mean Clustering, ...)***
- **Hybrid** ***(Genetic algorithms, Bayesian network, ...)***

Table 3.

Reservoir Data Fusion

- **Rockphysical**
  - transform seismic data to attributes and reservoir properties
  - formulate seismic/log/core data to reservoir properties
- **Geostatistical**
  - transform seismic attributes to formation characters
  - transform seismic attributes to reservoir properties
  - simulate the 2D/3D distribution of seismic and log attributes
- **Intelligent**
  - clustering anomalies in seismic/log data and attributes
  - ANN layers for seismic attribute and formation characters
  - supervised training model to predict unknown from existing
  - hybrid such as GA and SA for complicated reservoirs

Table 4.

Geostatistical vs. Intelligent

- Geostatistical
  - Data assumption: a certain probability distribution
  - Model: weight functions come from variogram trend, stratigraphic facies, and probability constraints
  - Simulation: Stochastic, not optimized
- Intelligent
  - Data automatic clustering and expert-guided segmentation
  - Classification of relationship between data and targets
  - Model: weight functions come from supervised training based on geological and stratigraphic information
  - Simulation: optimized by GA, SA, ANN, and BN

2.2 Intelligent Interpretation and Data Analysis

Once all the pertinent data is properly integrated (fused) one has to extract the relevant information from the data and draw the necessary conclusions. This can be done either true reliance on human expert or an intelligent system that has the capability to learn and modify its knowledge base as new information become available. For detailed review of various applications of soft computing in intelligent interpretation, data analysis and pattern recognition see Aminzadeh (1989), Aminzadeh (1991) and Aminzadeh and Jamshidi (1995).

Although seismic signal processing has advanced tremendously over the last four decades, the fundamental assumption of a "convolution model" is violated in many practical settings. Sven Treitel, in Aminzadeh (1995) was quoted to pose the question: *What if, mother earth refuses to convolve?* Among such situations are: highly heterogeneous environments, very absorptive media (such as unconsolidated sand and young sediments), fractured reservoirs, and mud volcano, karst and gas chimneys. In such cases we must consider non-linear processing and interpretation methods. Neural networks fractals, fuzzy logic, genetic algorithms, chaos and complexity theory are among such non-linear processing and analysis techniques that have been proven to be effective. The highly heterogeneous earth model that geophysics attempts to quantify is an ideal place for applying these concepts. The subsurface lives in a hyper-dimensional space (the properties can be considered as the additional space dimension), but its actual response to external stimuli initiates an internal coarse-grain and self-organization that results in a low-dimensional structured behavior. Fuzzy logic and other non-linear methods can describe shapes and structures generated by chaos. These techniques will push the boundaries of seismic resolution, allowing smaller-scale anomalies to be characterized.

2.3 Pattern Recognition

In the 1960s and 1970s, pattern recognition techniques were used only by statisticians and were based on statistical theories. Due to recent advances in computer systems and technology, artificial neural networks and fuzzy logic models have been used in many pattern recognition applications ranging from simple character recognition, interpolation, and extrapolation between specific patterns to the most sophisticated robotic applications. To recognize a pattern, one can use the standard multi-layer perceptron with a back-propagation learning algorithm or simpler models such as self-organizing networks (Kohonen, 1997) or fuzzy c-means techniques (Bezdek, 1981; Jang and Gulley, 1995). Self-organizing networks and fuzzy c-means techniques can easily learn to recognize the topology, patterns, or seismic objects and their distribution in a specific set of information. Much of the early applications of pattern recognition in the oil industry were highlighted at Aminzadeh, 1989.

2.4 Clustering

Cluster analysis encompasses a number of different classification algorithms that can be used to organize observed data into meaningful structures. For example, k-means is an algorithm to assign a specific number of centers, k, to represent the clustering of N points (k<N). These points are iteratively adjusted so that each point is assigned to one cluster, and the centroid of each cluster is the mean of its assigned points. In general, the k-means technique will produce exactly k different clusters of the greatest possible distinction.

Alternatively, fuzzy techniques can be used as a method for clustering. Fuzzy clustering partitions a data set into fuzzy clusters such that each data point can belong to multiple clusters. Fuzzy c-means (FCM) is a well-known fuzzy clustering technique that generalizes the classical (hard) c-means algorithm and can be used where it is unclear how many clusters there should be for a given set of data.

Subtractive clustering is a fast, one-pass algorithm for estimating the number of clusters and the cluster centers in a set of data. The cluster estimates obtained from subtractive clustering can be used to initialize iterative optimization-based clustering methods and model identification methods.

In addition, the self-organizing map technique known as Kohonen's self-organizing feature map (Kohonen, 1997) can be used as an alternative for clustering purposes. This technique converts patterns of arbitrary dimensionality (the pattern space) into the response of one- or two-dimensional arrays of neurons (the feature space). This unsupervised learning model can discover any relationship of interest such as patterns, features, correlations, or regularities in the input data, and translate the discovered relationship into outputs. The first application of clustering techniques to combine different seismic attributes was introduced in the mid eighties (Aminzadeh and Chatterjee, 1984)

2.5 Data integration and Reservoir property estimation

Historically, the link between reservoir properties and seismic and log data have been established either through "statistics-based" or "physics-based" approaches. The latter, also known as model based approaches attempt to exploit the changes in seismic character or seismic attribute to a given reservoir property, based on physical phenomena. Here, the key issues are sensitivity and uniqueness. Statistics based methods attempt to establish a heuristic relationship between seismic measurements and prediction values from examination of data only. It can be argued that a hybrid method, combining the strength of statistics and physics based method would be most effective. **Figure 3**, taken from Aminzadeh, 1999 shows the concepts schematically.

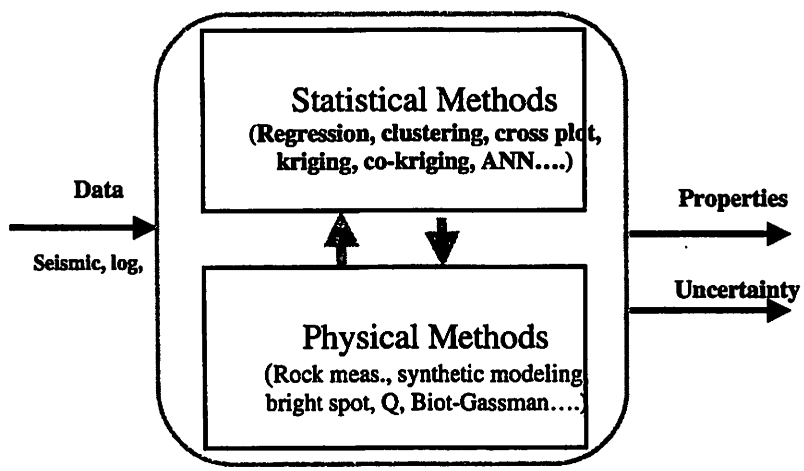


Figure 3. A schematic description of physics-based (blue), statistics-based (red) and hybrid method (green)

Many geophysical analysis methods and consequently seismic attributes are based on physical phenomena. That is, based on certain theoretical physics (wave propagation, Biot-Gassman Equation, Zoeppritz Equation, tuning thickness, shear wave splitting, etc.) certain attributes may be more sensitive to changes in certain reservoir properties. In the absence of a theory, using experimental physics (for example rock property measurements in a laboratory environment such as the one described in the last section of this paper) and/or numerical modeling, one can identify or validate suspected relationships. Although physics-based methods and direct measurements (the ground truth) is the ideal and reliable way to establish such correlations, for various reasons it is not always practical. Those reasons range from lack of known theories, difference between the laboratory environment and field environment (noise, scale, etc.) and the cost for conducting elaborate physical experiments.

Statistics-based methods aim at deriving an explicit or implicit heuristic relationship between measured values and properties to be predicted. Neural-networks and fuzzy-neural networks-based methods are ideally suitable to establish such implicit relationships through proper training. We all attempt to establish a relationship between different seismic attributes, petrophysical measurements, laboratory measurements and different reservoir properties. In such statistics-based method one has keep in mind the impact of noise on the data, data population used for statistical analysis, scale, geologic environment, scale and the correlation between different attributes when performing clustering or regressions. The statistics-based conclusions have to be reexamined and their physical significance explored.

2.6 Quantification of data uncertainty and prediction error and confidence interval

One of the main problems we face is to handle non-uniqueness issue and quantify uncertainty and confidence intervals in our analysis. We also need to understand the incremental improvements in prediction error and confidence range from introduction of new data or a new analysis scheme. Methods such as evidential reasoning and fuzzy logic are most suited for this purpose. **Figure 4** shows the distinction between conventional probability and theses techniques. "Point probability," describes the probability of an event, for example, having a commercial reservoir. The implication is we know exactly what this probability is. Evidential reasoning, provides an upper bound (plausibility) and lower bound (credibility) for the event the difference between the two bounds is considered as the ignorance range. Our objective is to reduce this range through use of all the new information. Given the fact that in real life we may have non-rigid boundaries for the upper and lower bounds and we ramp up or ramp down our confidence for an event at some point, we introduce fuzzy logic to handle and we refer to it as "membership grade". Next-generation earth modeling will incorporate quantitative representations of geological processes and stratigraphic / structural variability. Uncertainty will be quantified and built into the models.

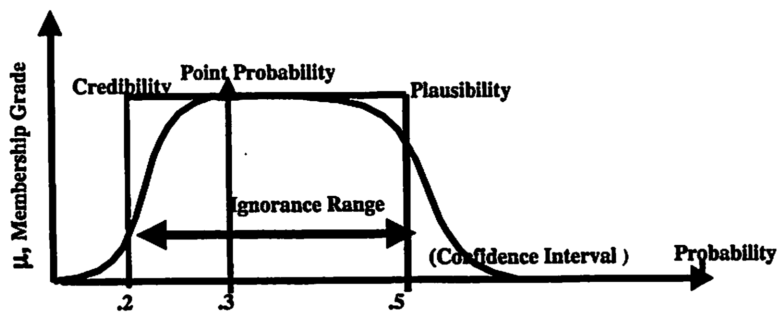
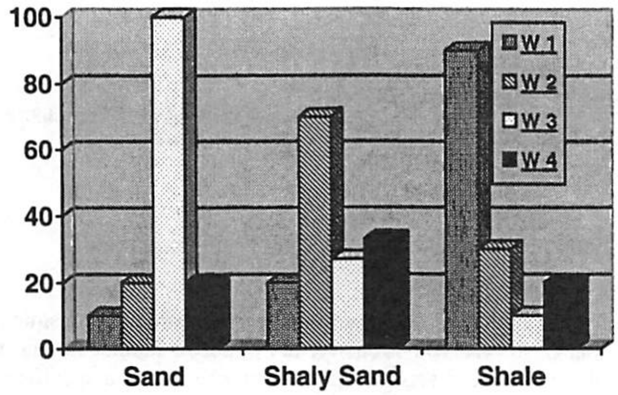


Figure 4. Point probability, evidential reasoning and fuzzy logic

On the issue of non-uniqueness, the more sensitive the particular seismic character to a given change to reservoir property, the easier to predict it. The more unique influence of the change in seismic character to changes in a specific reservoir property, the higher the confidence level in such predictions. Fuzzy logic can handle subtle changes in the impact of different reservoir properties on the wavelet response. Moreover comparison of multitude of wavelet responses (for example near, mid and far offset wavelets) is easier through use of neural networks. As discussed in Aminzadeh and de Groot, 2001, let us assume a seismic pattern for three different lithologies (sand, shaly sand and shale) are compared from different well information and seismic response (both model and field data) and the respective seismic character within the time window or the reservoir interval with four "classes" of wavelets, (w1, w2, w3.and w4). These 4 wavelets (basis wavelets) serve as a segmentation vehicle. The histograms in **Figure 5a** show what classes of wavelets that are likely to be present for given lithologies. In the extreme positive (EP) case we would have one wavelet uniquely representing one lithology. In the extreme negative case (EN) we would have a uniform distribution of all wavelets for all lithologies. In most cases unfortunately we are closer to NP than to EP. The question is how best we can get these distributions move from the EN side to EP side thus improving our prediction capability and increasing confidence level. The common sense is to add enhance information content of the input data.

How about if we use wavelet vectors comprised of pre-stack data (in the simple case, mid, near far offset data) as the input to a neural network to perform the classification? Intuitively, this should lead to a better separation of different lithologies (or other reservoir properties). Likewise, including three component data as the input to the classification process would further improve the confidence level. Naturally, this requires introduction of a new "metric" measuring "the similarity" of these "wavelet vectors". This can be done using the new basis wavelet vectors as input to a neural network applying different weights to mid, near and far offset traces. This is demonstrated conceptually, in **Figure 5** to predict lithology. Compare the sharper histograms of the vector wavelet classification (in this case, mid, near, and far offset gathers) in **Figure 5b**, against those of **Figure 5a** based on scalar wavelet classification.



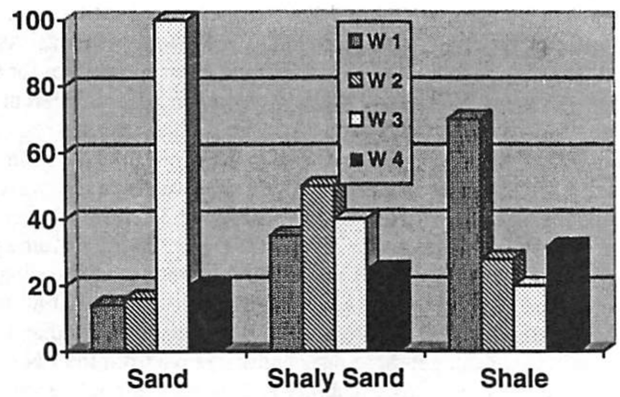


Figure 5- Statistical distribution of different wavelet types versus lithologies, A, -pre-stack data. B, stacked data

3 Artificial Neural Network and Geoscience Applications of ANN for Exploration

Although Artificial neural networks (ANN) were introduced in the late fifties (Rosenblatt, 1962), the interests in them have been increasingly growing in recent years. This has been in part due to new applications fields in the academia and industry. Also, advances in computer technology (both hardware and software) have made it possible to develop ANN capable of tackling practically meaningful problems with a reasonable response time. Simply put, neural networks are computer models that attempt to simulate specific functions of human nervous system. This is accomplished through some parallel structures comprised of non-linear processing nodes that are connected by fixed (Lippmann, 1987), variable (Barhen et al., 1989) or fuzzy (Gupta and Ding, 1994) weights. These weights establish a relationship between the inputs and output of each "Neuron" in the ANN. Usually ANN have several "hidden" layers each layer comprised of several neurons. If the feed-forward (FF) network (FF or concurrent networks are those with unidirectional data flow). The full technical details can be found in Bishop (Bishop, 1995). If the FF network is trained by back propagation (BP) algorithms, they are called BP. Other types of ANN are supervised (self organizing) and auto (hetro) associative networks.

Neurocomputing represents general computation with the use of artificial neural networks. An artificial neural network is a computer model that attempts to mimic simple biological learning processes and simulate specific functions of human nervous system. It is an adaptive, parallel information processing system which is able to develop associations, transformations or mappings between objects or data. It is also the most popular intelligent technique for pattern recognition to date.

The major applications of neurocomputing are seismic data processing and interpretation, well logging and reservoir mapping and engineering.

Good quality seismic data is essential for realistic delineation of reservoir structures. Seismic data quality depends largely on the efficiency of data processing. The processing step is time consuming and complex. The major applications include first arrival picking, noise elimination, structural mapping, horizon picking and event tracking. A detailed review can be found in Nikravesh and Aminzadeh (1999).

For interwell characterization, neural networks have been used to derive reservoir properties by crosswell seismic data. In Chawathé et al. (1997), the authors used a neural network to relate five seismic attributes (amplitude, reflection strength, phase, frequency and quadrature) to gamma ray (GR) logs obtained at two wells in the Sulimar Queen field (Chaves County). Then the GR response was predicted between the wells and was subsequently converted to porosity based on a field-specific porosity-GR transform. The results provided good delineation of various lithofacies.

Feature extraction from 3D seismic attributes is an extremely important area. Most statistical methods are failed due to the inherent complexity and nonlinear information content. **Figure 3** shows an example use of neural networks for segmenting seismic characters thus deducing information on the seismic facies and reservoir properties (lithology, porosity, fluid saturation and sand thickness). A display of the level of confidence (degree of match) between the seismic character at a given point versus the representative wavelets (centers of clusters) is also shown. Combining this information with the seismic model derived from the well logs while perturbing for different properties gives physical meaning of different clusters.

Monson and Pita (1997) applied neural networks to find relationships between 3D seismic attributes and well logs. The study provided realistic prediction of log responses far away from the wellbore. Boadu (1997) also used similar technology to relate seismic attributes to rock properties for sandstones. In Nikravesh et al.[7], the author applied a combination of k-means clustering, neural networks and *fuzzy c-means (1984)* (a clustering algorithm in which each data vector belongs to each of the clusters to a degree specified by a membership grade) techniques to characterize a field that produces from the Ellenburger Dolomite. The techniques were used to perform clustering of 3D seismic attributes and to establish relationships between the clusters and the production log. The production log was established away from wellbore. The production log and the clusters were then superimposed at each point of a 3D seismic cube. They also identified the optimum locations for new wells based on the connectivity, size and shape of the clusters related to the pay zones.

The use of neural networks in well logging has been popular for nearly one decade. Many successful applications have been documented (Wong et al., 1998; Brus et al., 1999; Wong et al., 2000). The most recent work by Bruce et al. (2000) presented a state-of-the-art review of the use of neural networks for predicting permeability from well logs. In this application, the network is used as a nonlinear regression tool to develop transformation between well logs and core permeability. Such a transformation can be used for estimating permeability in uncored intervals and wells. In this work, the permeability profile was predicted by a Bayesian neural network. The network was trained by a training set with four well logs (GR, NPHI, RHOB and RT) and core permeability. The network also provided a measure of confidence (the standard deviation of a Gaussian function): the higher the standard deviation ("sigma"), the lower the prediction reliability. This is very useful for understanding the risk of data extrapolation. The same tool can be applied to estimate porosity and fluid saturations. Another important application is the clustering of well logs for the recognition of lithofacies (Rogers et al., 1992). This provides useful information for improved petrophysical estimates and well correlation.

Neurocomputing has also been applied to reservoir mapping. In Wong et al.(1997) and Wang et al.(1998, 1999, 1999), the authors applied a radial basis function neural network to relate the conceptual distribution of geological facies (in the form of hand drawings) to reservoir porosity. It is able to incorporate the general property trend provided by local geological knowledge and to simulate fine-scaled details when used in conjunction with geostatistical simulation techniques. In Caers (1999) and Caers and Journel (1998), the authors trained a neural network to recognize the local conditional probability based on multiple-point information retrieved from a "training image," which can be any densely populated image (e.g. outcrop data, photographs, hand drawings, seismics, etc.). The conditional probability was used in stochastic simulation with a Markov Chain sampler (e.g. Markov Chain Monte Carlo). These methodologies can be applied to produce 3D model of petrophysical properties using multiple seismic attributes and conceptual geological maps. This is a significant advantage compared to the conventional geostatistical methods which are limited to two-point statistics (e.g. variograms) and simple objects (e.g. channels).

In Nikravesh et al.(1996), the authors used neural networks to predict field performance and optimize oil recovery by water injection in the Lost Hill Diatomite (Kern County). They constructed several neural networks to model individual well behavior (wellhead pressure and injection-production history) based on data obtained from the surrounding wells. The trained networks were used to predict future fluid production. The results matched well with the actual data. The study also led to the best oil recovery with the minimum water injected.

In what follows we will review the geoscience applications in these broad areas: Data Processing and Prediction. We will not address other geoscience applications such as: classification of multi- source remote sensing data Bennediktson et. al., (1990), earthquake prediction, Aminzadeh et. al. (1994), and ground water remediation, Johnson and Rogers (1995).

3.1 Data Processing

Various types of geoscience data are used in the oil industry to ultimately locate the most prospective locations for oil and gas reservoirs. These data sets go through extensive amount of processing and manipulation before they are analyzed and interpreted. The processing step is very time consuming yet a very important one. ANN have been utilized to help improve the efficiency of operation in this step. Under this application area we will examine: First seismic arrival picking, and noise elimination problems. Also, see Aminzadeh (1991) and McCormack (1991) and Zadeh Aminzadeh (1995) and Aminzadeh et al (1999) for other related applications.

3.1.1 First Arrival Picking

Seismic data are the response of the earth to any disturbance (compressional waves or shear waves). The seismic source can be generated either artificially (petroleum seismology, PS) or, naturally, (earthquake seismology, ES). The recorded seismic data are then processed and analyzed to make an assessment of the subsurface (both the geological structures and rock properties) in PS and the nature of the source (location or epicenter and magnitude, for example, in Richter scale) in ES. Conventional PS relies heavily on compressional (P- wave) data while ES is essentially based on the shear (S- wave) data.

The first arrivals of P and S waves on a seismic record contain useful information both in PS and ES. However one should make sure that the arrival is truly associated with a seismically generated event not a noise generated due to various factors. Since we usually deal with thousands of seismic records, their visual inspection for distinguishing FSA from noise, even if reliable, could be quite time consuming.

One of the first geoscience applications of ANN has been to streamline the operation of identifying the FSA in an efficient and reliable manner. Among the recent publications in this area are: McCormack (1990) and Veezhinathan et al. (1991). Key elements of the latter (V91) are outlined below:

Here, the FSA picking is treated as a pattern recognition problem. Each event is classified either as an FSA or non-FSA. A segment of the data within a window is used to obtain four "Hilbert" attributes of the seismic signal. The Hilbert attributes of seismic data were introduced by Taner et al. (1979). In V91, these attributes are derived from seismic signal using a sliding time window. Those attributes are: 1) Maximum Amplitude, 2) Mean Power Level; MPL, 3) Power Ratios, and 4) Envelop Slop Peak. These types of attributes have been used by Aminzadeh and Chatterjee (1984) for predicting gas sands using clustering and discernment analysis technique.

In V91, the network processes three adjacent peaks at a time to decide whether the center peak is an FSA or a non-FSA. A BPN with five hidden layers combined with a post processing scheme accomplished correct picks of 97%. Adding a fifth attribute, Distance from Travel Time Curve, generated satisfactory results without the need for the post processing step.

McCormack (1990) created a binary image from the data and used it to train the network to move up and down across the seismic record to identify the

FSA. This image-based approach captures space-time information in the data but requires a large number of input units, thus necessitating a large network. Some empirical schemes are used to ensure its stability.

3.1.2 Noise Elimination

A related problem to FSA is editing noise from the seismic record. The objective here is to identify events with non-seismic origin (the reverse of FSA) and then remove them from the original data in order to increase the signal to noise ratio. Liu et al. (1989), McCormack (1990) and Zhang and Li (1994) are Some of the publications in this area.

Zhang and Li (1994) handled the simpler problem, to edit out the whole noisy trace from the record. They initiate the network in the "learning" phase by "scanning " over the whole data set. The weights are adapted in the learning phase either with some human input as the distinguishing factors between "good" and "bad" traces or during an unsupervised learning phase. Then in the "recognizing" phase the data are scanned again and depending upon whether the output of the network is less than or greater than a threshold level the trace is either left alone or edited out as a bad trace.

3.2 Identification and Prediction

Another major application area for ANN in the oil industry is to predict various reservoir properties. This ultimately is used a decision tool for exploration and development drilling and redevelopment or extension of the existing fields. The input data to this prediction problem is usually processed and interpreted seismic and log data and/or a set of attributes derived from the original data set. Historically, many "hydrocarbon indicators" have been proposed to make such predictions. Among them are: the bright spot analysis Sherif and Geldart (1982), amplitude versus offset analysis, Ostrander (1982), seismic clustering analysis, Aminzadeh and Chatterjee (1984),fuzzy pattern recognition, Griffiths (1987) and other analytical methods, Agterberg and Griffiths (1991). Many of the ANN developed for this purpose are built around the earlier techniques either for establishing a relationship between the raw data and physical properties of the reservoirs and/or to train the network using the previously established relationships.

Huang and Williamson (1994) have developed a general regression neural network, GRNN to predict rock's total organic carbon (TOC) using well log data.

First, they model the relationship between the resistivity log and TOC with a GRNN, using published data. After training the ANN in two different modes, the GRNN found optimum values of sigma. Sigma is an important smoothing parameter used in GRNN. They have established the superiority of GRNN over BP-ANN in determining the architecture of the network. After completing the training phase a predictive equation for determining TOC was derived. Gogan et al (1995) used ANN for determining lithology and fluid saturation from well log and pre-stack seismic data. Various seismic attributes from partial stacks (mid, near and far offsets) as an input to ANN. The network was calibrated using synthetic (theoretical) data with pre stack seismic response of known lithologies and saturation from the well log data. The output of the network was a set of classes of lithologies and saturations.

3.3 Neural Network and Nonlinear Mapping

In this section, a series of neural network models will be developed for nonlinear mapping between wireline logs. A series of neural network models will also be developed to analyze actual welllog data and seismic information and the nonlinear mapping between wireline logs and seismic attributes will be recognized.

In this study, wireline logs such as travel time (DT), gamma ray (GR), and density (RHOB) will be predicted based on SP, and resistivity (RILD) logs. In addition, we will predict travel time (DT) based on induction resistivity and vice versa. In this study, all logs are scaled uniformly between -1 and 1 and results are given in scaled domain.

Figures 6A through 6E show typical behavior of SP, RILD, DT, GR, and RHOB logs in scaled domain. The design of a neural network to predict DT, GR, and RHOB based on RILD and SP logs starts with filtering, smoothing, and interpolating values (in a small horizon) for missing information in the data set. A first-order filter and a simple linear recursive parameter estimator for interpolating were used to filter and reconstruct the noisy data. The available data were divided into three data sets: training, testing, and validation. The network was trained based on the training data set and continuously tested using a test data set during the training phase. The network was trained using a backpropagation algorithm and modified Levenberge-Marquardt optimization technique. Training was stopped when prediction deteriorated with step.

3.3.1 Travel time (DT) prediction based on SP and resistivity (RILD) logs.

The neural network model to predict the DT has 14 input nodes (two windows of data each with 7 data points) representing SP (7 points or input nodes) and RILD (7 points or input nodes) logs. The hidden layer has 5 nodes. The output layer has 3 nodes representing the prediction of the DT (a window of 3 data point). Typical performance of the neural network for training, testing, and validation data sets is

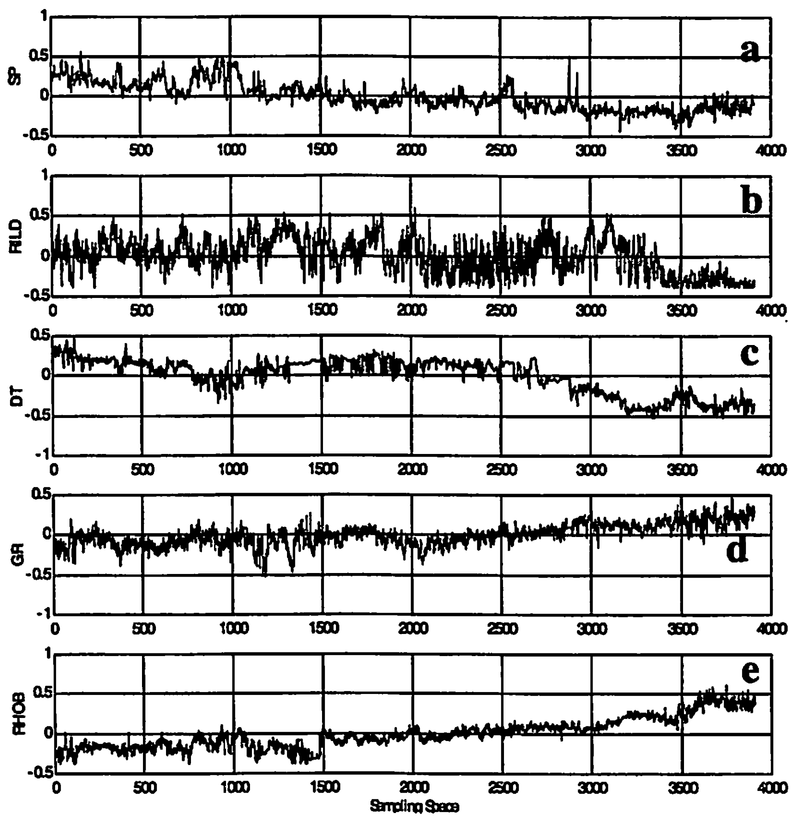
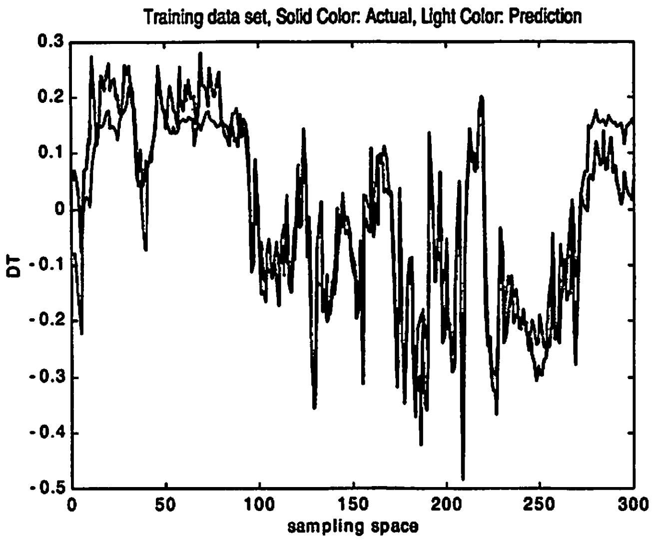


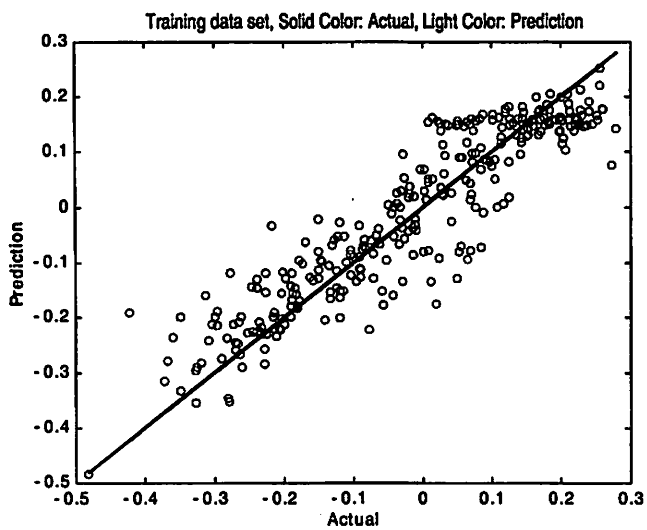
Figure 6. Typical behavior of SP, RILD, DT, GR, and RHOB logs.

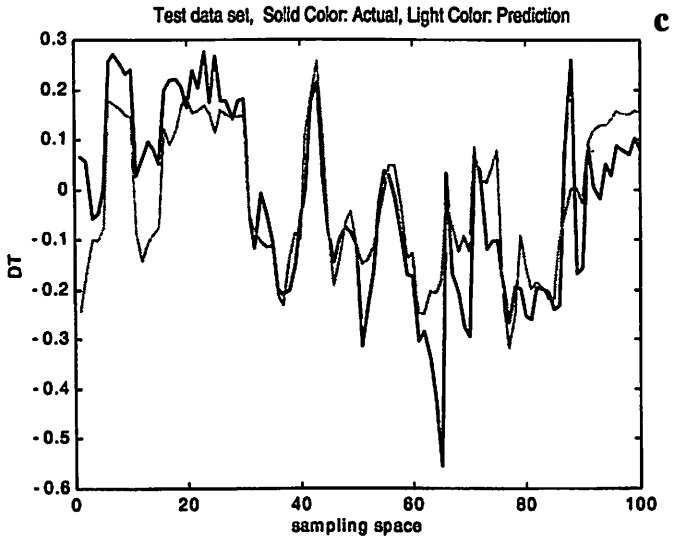
shown in **Figures 7A, 7B, 7C,** and **7D.** The network shows good performance for prediction of DT for training, testing, and validation data sets. However, there is not a perfect match between actual and predicted values for DT is the testing and validation data sets. This is due to changes of the lithology from point to point. In other words, some of the data points in the testing and validation data sets are in a lithological layer which was not presented in the training phase. Therefore, to have perfect mapping, it would be necessary to use the layering information (using other types of logs or linguistic information) as input into the network or use a lar

a


Training data set, Solid Color: Actual, Light Color: Prediction
DT
sampling space
0.3
0.2
0.1
0
-0.1
-0.2
-0.3
-0.4
-0.5
0
50
100
150
200
250
300

b


Training data set, Solid Color: Actual, Light Color: Prediction
Prediction
Actual
0.3
0.2
0.1
0
-0.1
-0.2
-0.3
-0.4
-0.5
-0.5
-0.4
-0.3
-0.2
-0.1
0
0.1
0.2
0.3



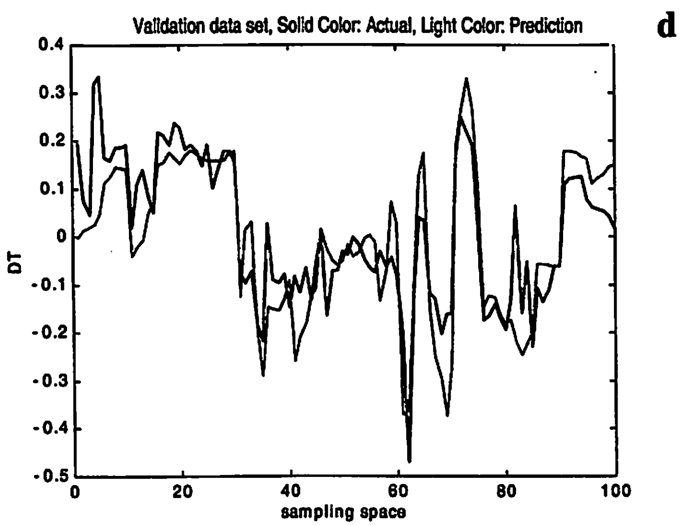


Figure 7. Typical neural network performance for prediction of DT based on SP and RILD.

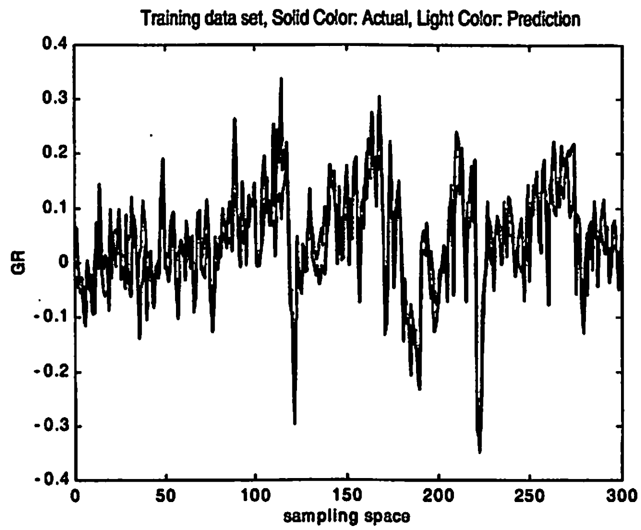
ger data set for the training data set which represent all the possible behaviors in the data.

3.3.2 Gamma ray (GR) prediction based on SP and resistivity (RILD) logs.

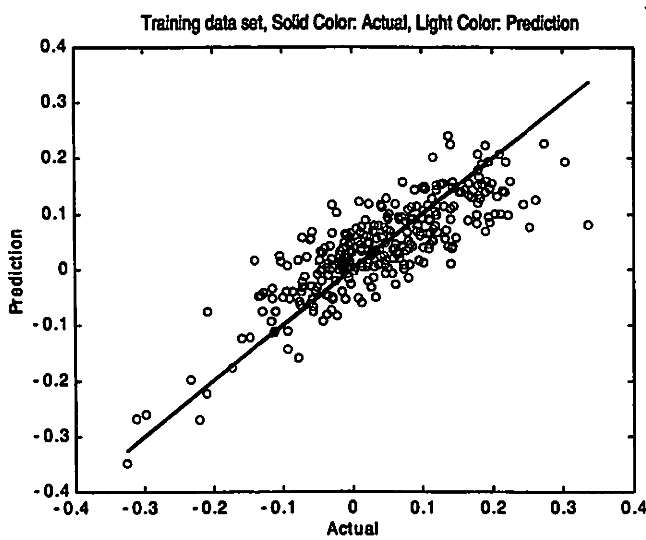
In this study, a neural network model is developed to predict GR based on SP and RILD log. The network has 14 input nodes (two windows of data, each with 7 data points) representing SP (7 points or input nodes) and RILD (7 points or input nodes) logs. The hidden layer has 5 nodes. The output layer has 3 nodes representing the prediction of the GR. **Figures 8A** through **8D** show the performance of the neural network for training, testing, and validation data. The neural network model shows a good performance for prediction of GR for training, testing, and validation data sets. In comparison with previous studies (DT prediction), this study shows that the GR is not as sensitive as DT to noise in the data. In addition, a better global relationship exits between SP-resisitivity-GR rather than SP-resisitivity-DT. However, the local relationship is in the same order of complexity. Therefore, two models have the same performance for training (excellent performance). However, the model for prediction of GR has a better generalization property. Since the two models have been trained based on the same criteria, it is unlikely that this lack of mapping for generalization is due to over fitting during the training phase.

3.3.3 Density (RHOB) prediction based on SP and resistivity (RILD) logs.

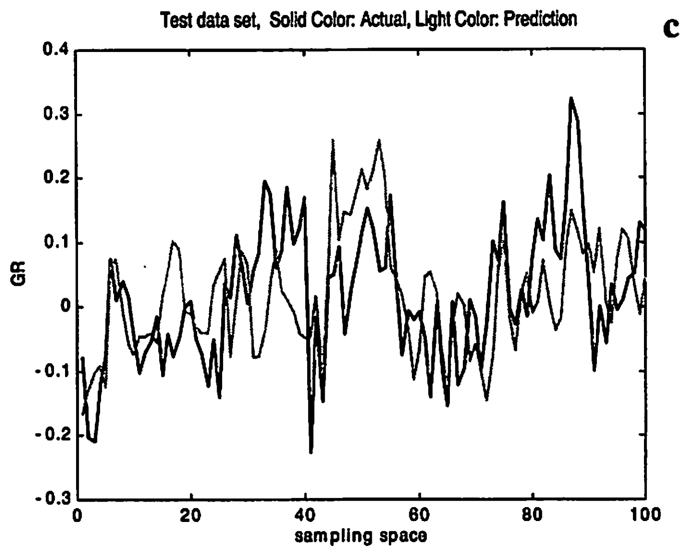
To predict density based on SP and RILD logs, a neural network model with 14 input nodes representing SP (7 points or input nodes) and RILD (7 points or input nodes) logs, 5 nodes in the hidden layer, and 3 nodes in the output layer representing the prediction of the RHOB is developed. **Figures 9A** through **9D** show a typical performance of the neural network for the training, testing, and validation data sets. The network shows excellent performance for the training data set as shown in **Figures 9A** and **9B**. The model shows a good performance for the testing data set as shown in **Figure 9C**. **Figure 9D** shows the performance of the neural network for the validation data set. The model has relatively good performance for the validation data set. Therefore, there is not a perfect match between the actual and predicted values for RHOB for the testing and validation data set. Since RHOB is directly related to lithology and layering, and to have perfect mapping, it would be necessary to use the layering information (using other types of logs or linguistic information) as an input into the network or use a larger data set for the training


Training data set, Solid Color: Actual, Light Color: Prediction
GR
sampling space
0.4
0.3
0.2
0.1
0
-0.1
-0.2
-0.3
-0.4
0
50
100
150
200
250
300

a


Training data set, Solid Color: Actual, Light Color: Prediction
Prediction
Actual
0.4
0.3
0.2
0.1
0
-0.1
-0.2
-0.3
-0.4
-0.4
-0.3
-0.2
-0.1
0
0.1
0.2
0.3
0.4

b



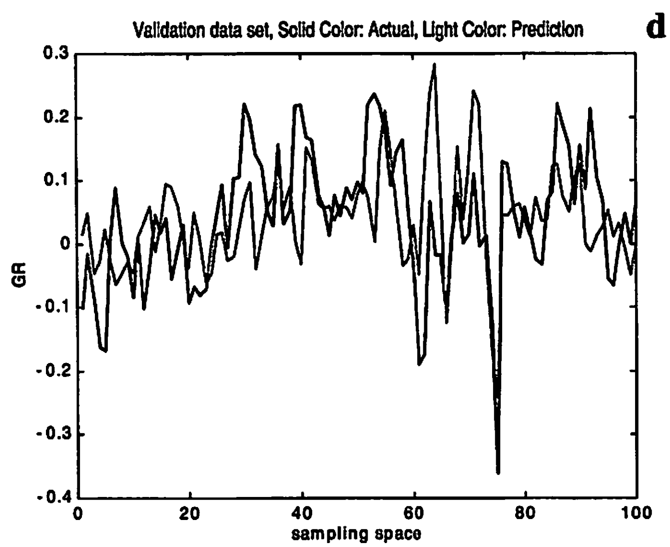
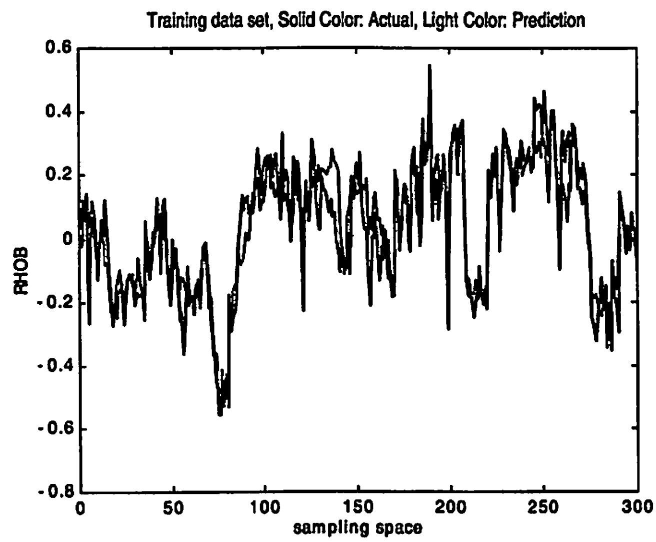
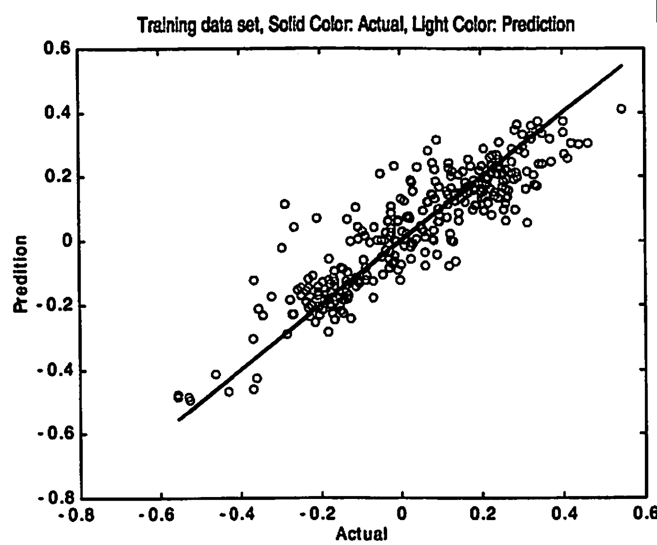


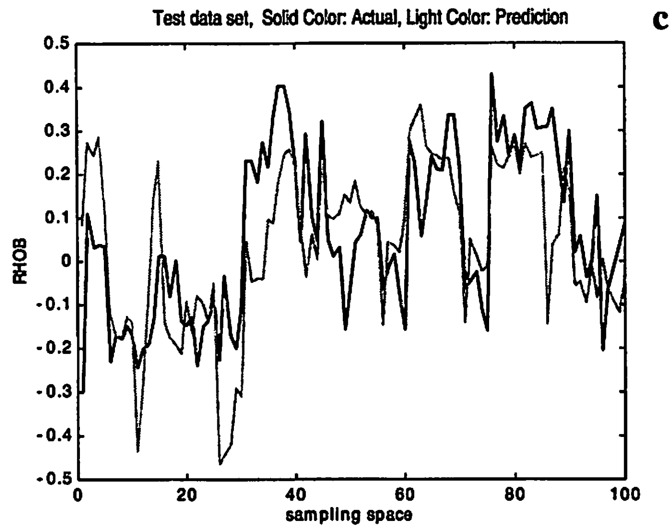
Figure 8. Typical neural network performance for prediction of GR based on SP and RILD.


Training data set, Solid Color: Actual, Light Color: Prediction
RHOB
sampling space
0.6
0.4
0.2
0
-0.2
-0.4
-0.6
-0.8
0
50
100
150
200
250
300

a


Training data set, Solid Color: Actual, Light Color: Prediction
Predition
Actual
0.6
0.4
0.2
0
-0.2
-0.4
-0.6
-0.8
-0.8
-0.6
-0.4
-0.2
0
0.2
0.4
0.6

b



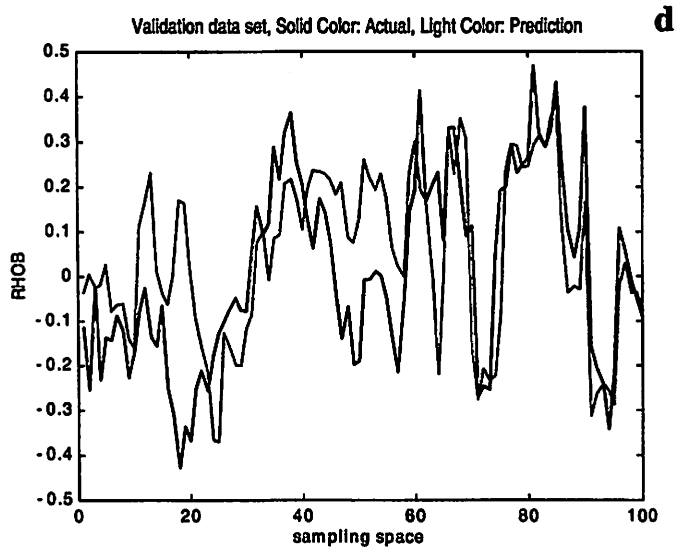


Figure 9. Typical neural network performance for prediction of RHOB based on SP and RILD.

data set which represent all the possible behaviors in the data. In these cases, one can use a knowledge-based approach using knowledge of an expert and select more diverse information which represent all different possible layering as a training data set. Alternatively, one can use an automated clustering technique to recognize the important clusters existing in the data and use this information for selecting the training data set.

3.3.4 Travel time (DT) prediction based on resistivity (RILD).

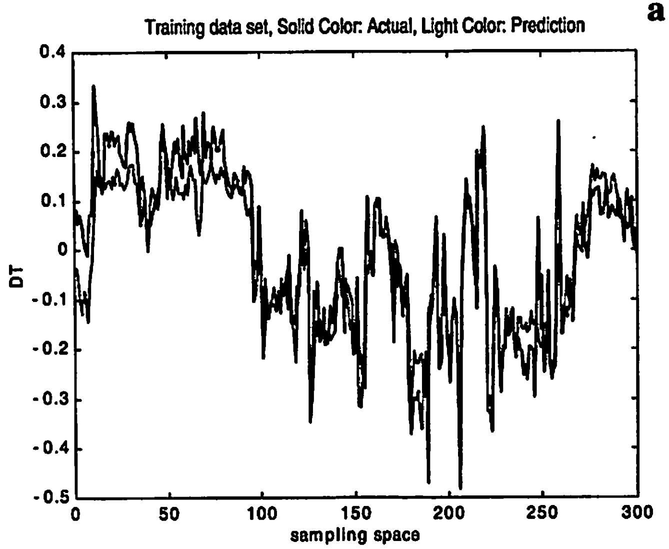
The neural network model to predict the DT has 11 input nodes representing a RILD log. The hidden layer has 7 nodes. The output layer has 3 nodes representing the prediction of the DT. Using engineering knowledge, a training data set is carefully selected so as to represent all the possible layering existing in the data. The typical performance of neural network for the training, testing, and validation data sets is shown in **Figures 10A** through **10D**. As expected, the network has excellent performance for prediction of DT. Even though only RILD logs are used for prediction of DT, the network model has better performance than when SP and RILD logs used for prediction of DT (comparing **Figures 7A** through **7D** with **5A** through **5D**). However, in this study, knowledge of an expert was used as extra information. This knowledge not only reduced the complexity of the model, but also better prediction was achieved.

3.3.5 Resistivity (RILD) prediction based on travel time (DT)

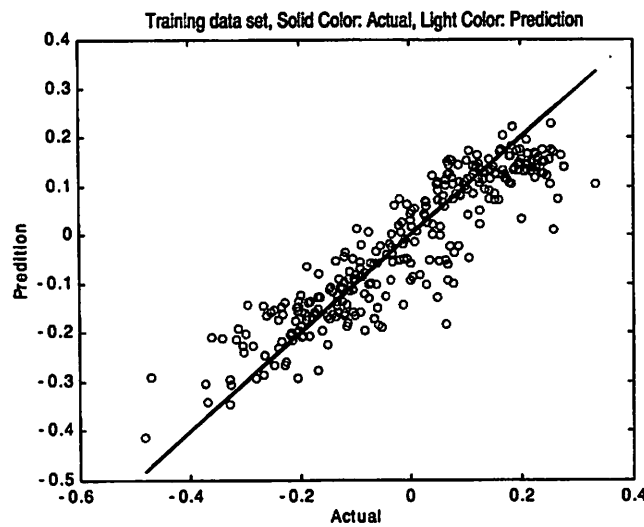
In this section, to show that the technique presented in the previous section is effective, the performance of the inverse model is tested. The network model has 11 input nodes representing DT, 7 nodes in the hidden layer, and 3 nodes in the output layer representing the prediction of the RILD. **Figures 11A** through **11D** show the performance of the neural network model for the training, testing, and validation data sets. **Figures 11A** and **11B** show that the neural network has excellent performance for the training data set. **Figures 6C** and **6D** show the performance of the network for the testing and validation data set. The network shows relatively excellent performance for testing and validation purposes. As was mentioned in the previous section, using engineering knowledge the complexity of the model was reduced and better performance was achieved.

In addition, since the network model (prediction of DT from resisitivity) and its inverse (prediction of resisitivity based on DT) have relatively excellent

a


Training data set, Solid Color: Actual, Light Color: Prediction
DT
sampling space
0.4
0.3
0.2
0.1
0
-0.1
-0.2
-0.3
-0.4
-0.5
0
50
100
150
200
250
300

b


Training data set, Solid Color: Actual, Light Color: Prediction
Predition
Actual
0.4
0.3
0.2
0.1
0
-0.1
-0.2
-0.3
-0.4
-0.5
-0.6
-0.4
-0.2
0
0.2
0.4

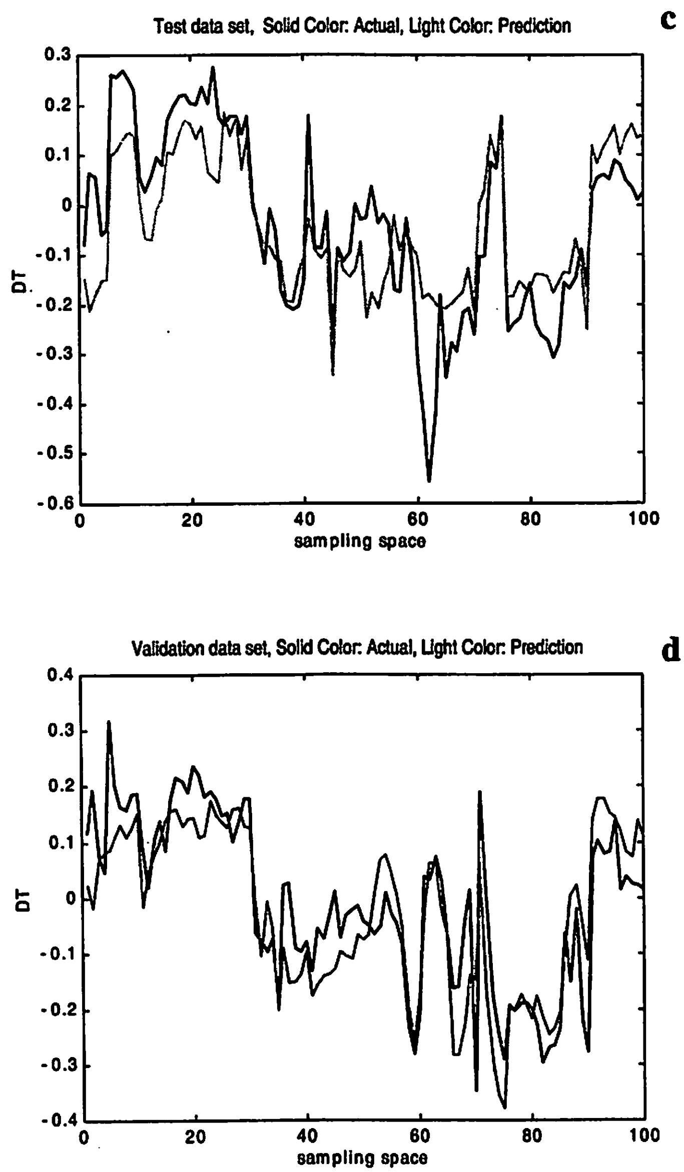
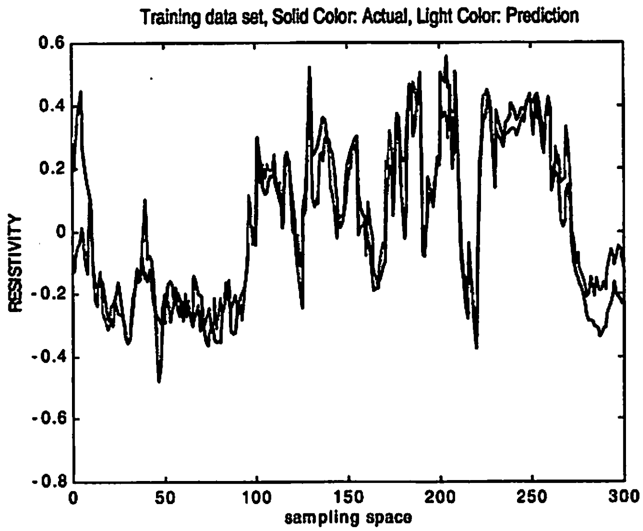
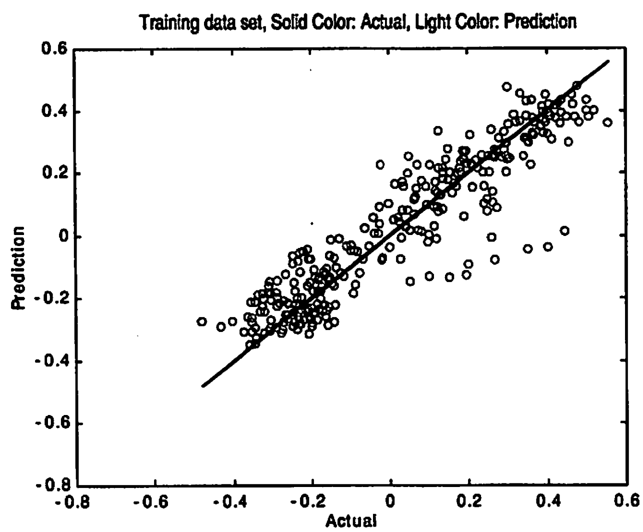


Figure 10. Typical neural network performance for prediction of DT based on RILD.

a


Training data set, Solid Color: Actual, Light Color: Prediction
RESISTIVITY
sampling space
0.6
0.4
0.2
0
-0.2
-0.4
-0.6
-0.8
0
50
100
150
200
250
300

b


Training data set, Solid Color: Actual, Light Color: Prediction
Prediction
Actual
0.6
0.4
0.2
0
-0.2
-0.4
-0.6
-0.8
-0.8
-0.6
-0.4
-0.2
0
0.2
0.4
0.6

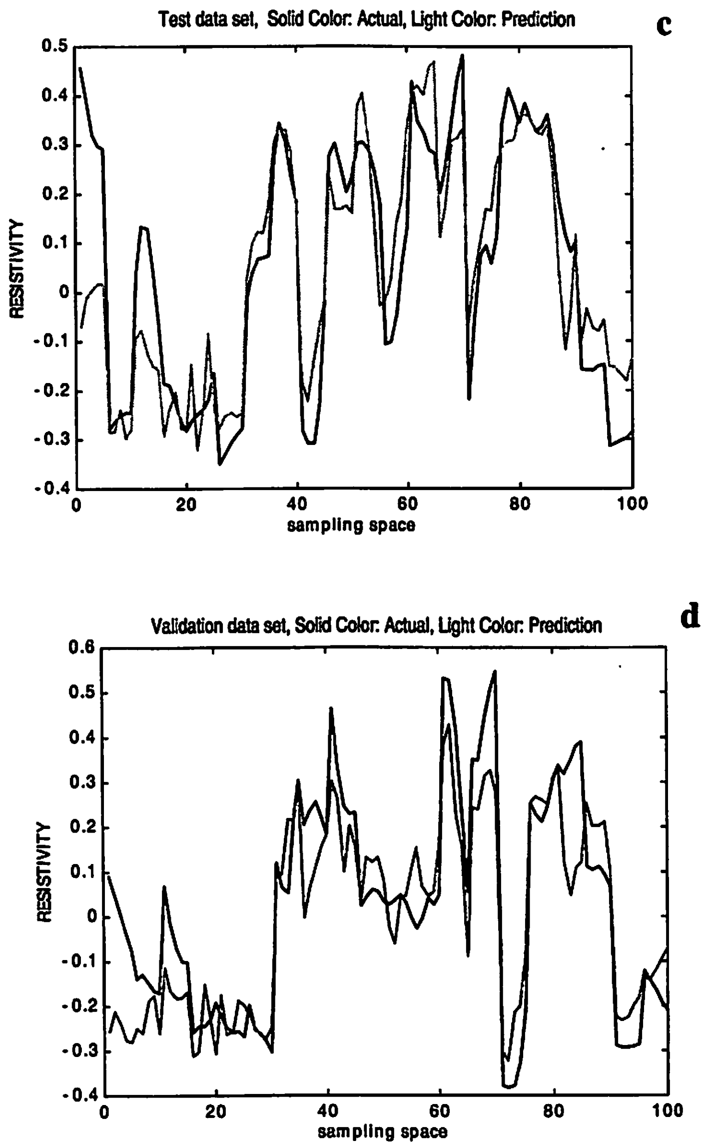


Figure 11. Typical neural network performance for prediction of RILD based on DT.

performance and generalization properties, a one-to-one mapping was achieved. Therefore, this implies that a good representation of layering was selected based on knowledge of an expert.

4 Fuzzy Logic

In recent years, it has been shown that uncertainty may be due to fuzziness rather than chance. Fuzzy logic is considered to be appropriate to deal with the nature of uncertainty in system and human error, which are not included in current reliability theories. The basic theory of fuzzy sets was first introduced by Zadeh (1965). Unlike classical logic which is based on crisp sets of "true and false", fuzzy logic views problems as a degree of "truth", or "fuzzy sets of true and false" (Zadeh 1965). Despite the meaning of the word "fuzzy", fuzzy set theory is not one that permits vagueness. It is a methodology that was developed to obtain an approximate solution where the problems are subject to vague description. In addition, it can help engineers and researchers to tackle uncertainty, and to handle imprecise information in a complex situation. During the past several years, the successful application of fuzzy logic for solving complex problems subject to uncertainty has greatly increased and today fuzzy logic plays an important role in various engineering disciplines. In recent years, considerable attention has been devoted to the use of hybrid neural network-fuzzy logic approaches as an alternative for pattern recognition, clustering, and statistical and mathematical modeling. It has been shown that neural network models can be use to construct internal models that capture the presence of fuzzy rules. However, determination of the input structure and number of membership functions for the inputs has been one of the most important issues of fuzzy modeling.

Fuzzy logic provides a completely new way of modeling complex and ill-defined systems. The major concept of fuzzy logic is the use of a *linguistic variable*, that is a variable whose values are words or sentences in a natural or synthetic language. This also leads to the use of *fuzzy if-then rules*, in which the antecedent and consequents are propositions containing linguistic variables.

In recent years, fuzzy logic, or more generally, fuzzy set theory, has been applied extensively in many reservoir characterization studies. This is mainly due to the fact that reservoir geology is mainly a descriptive science which uses mostly uncertain, imprecise, ambiguous and linguistic information (Bois 1984). Fuzzy set theory has the ability to deal with such information and to combine them with the quantitative observations. The applications are many, including seismic and stratigraphic modeling and formation evaluation.

In Bois (1984), he proposed to use fuzzy set theory as a pattern recognition tool to interpret a seismic section. The algorithm produced a synthetic seismic section by convoluting a geological model with a representative impulse (by deconvolution or signature of the source), which were both of subjective and fuzzy nature. The synthetic section was then compared with the original seismic section in a fuzzy context. In essence, the algorithm searches for the appropriate geological model from the observed seismic section by an iterative procedure, which is a popular way for solving inverse problems.

In Baygun et al.(1985), the authors used fuzzy logic as a classifier for the delineation of geological objects in a mature hydrocarbon reservoir with many wells. The authors showed that fuzzy logic can be used to extract dimensions and orientation of geological bodies, and geologists can use such a technique for reservoir characterization in a practical way which bypassed many tedious steps.

In Nordlund (1996), the author presented a study on dynamic stratigraphic modeling using fuzzy logic. In stratigraphic modeling, it is possible to model several processes simultaneously in space and time. Although many processes can be modeled using conventional mathematics, modeling the change of deposition and erosion on surfaces is often difficult. Formalizing geological knowledge is a difficult exercise as it involves handling of several independent and complex parameters. In addition, most information is qualitative and imprecise, which are unacceptable for direct numerical treatment. In the paper, the author showed a successful use of fuzzy rules to model erosion and deposition. The fuzzified variables included the depth of the reservoirs, the distances to source and shore, a sinusoidal sea-level curve, tectonic subsidence rate and simulation time with depositional surface. From the study, the author demonstrated that a few (10) fuzzy rules could produce stratigraphies with realistic geometry and facies.

In Cuddy (1997), the author applied fuzzy logic to solve a number of petrophysical problems in several North Sea fields. The work included lithofacies and permeability from well logs. Lithofacies prediction was based on the use of a possibility value (Gaussian function with a specific mean and variance) to represent a well log belonging to a certain lithofacies. The lithofacies that was associated with the highest combined fuzzy possibility (multiplication of all values) was taken as the most likely lithofacies for that set of logs. A similar methodology was applied to predict permeability by dividing the core permeability values into ten equal bin sizes on a log scale. The problem was converted into a classification problem. All the results suggested that the fuzzy approach had given better petrophysical estimates compared to the conventional techniques.

Fang and Chen (1997) also applied fuzzy rules to predict porosity and permeability from five compositional and textural characteristics of sandstone in the Yacheng Field (South China Sea). The five input attributes were the relative amounts of rigid grains, ductile grains and detrital matrix, grain size and the Trask sorting coefficient. All the porosity and permeability data were firstly divided into certain number of clusters by fuzzy c-means. The corresponding sandstone characteristics for each cluster were used to general the fuzzy linguistic rules. Each fuzzy cluster produced one fuzzy if-then rule with five input statements. The formulated rules were then used to make linguistic prediction by combining individual conclusion from each rule. If a numerical output was desired, a *defuzzification algorithm (1997)* could be used to extract a crisp output from a fuzzy set. The results showed that the fuzzy modeling gave better results compared to those presented in Bloch (1991).

In Huang et al.(1999), the authors presented a simple but practical fuzzy interpolator for predicting permeability from well logs in the North West Shelf (offshore Australia). The basic idea was to simulate local fuzzy reasoning. When a new input vector (well logs) was given, the system would select two training vectors which were nearest to the new input vector and build a set of piece-wise linear inference rules with the training values, in which the membership value of the training values was one. The study used well log and core data from two wells and the performance was tested at a third well, where actual core data were available for comparison. The accuracy of the permeability predictions at the test well was although similar to that obtained from the authors' previous neural-fuzzy technique, the fuzzy approach was >7,000 times faster in terms of CPU time.

In Nikravesh and Aminzadeh (2000), the authors applied a neural-fuzzy approach to develop an optimum set of rules for nonlinear mapping between porosity, grain size, clay content, P-wave velocity, P-wave attenuation and permeability. The rules developed from a training set were used to predict permeability in another data set. The prediction performance was very good. The study also showed that the integrated technique discovered clear relationships between P-wave velocity and porosity, and P-wave attenuation and clay content, which were useful to geophysicists.

4.1 Geoscience Applications of Fuzzy Logic

The uncertain, fuzzy, and linguistic nature of geophysical and geological data makes it a good candidate for interpretation through fuzzy set theory. The main advantage of this technique is in combining the quantitative data and qualitative information and subjective observation. The imprecise nature of the information available for interpretation (such as seismic data, wirelin logs, geological and lithological data) makes fuzzy sets theory an appropriate tool to utilize. For example, Chappaz (1977) and Bois (1983, 1984) proposed to use fuzzy sets theory in the interpretation of seismic sections. Bois used fuzzy logic as pattern recognition tool for seismic interpretation and reservoir analysis. He concluded that fuzzy set theory, in particular, can be used for interpretation of seismic data which are imprecise, uncertain, and include human error. He maintained these type of error and fuzziness cannot be taken into consideration by conventional mathematics. However, they are perfectly seized by fuzzy set theory. He also concluded that using fuzzy set theory one can determine the geological information using seismic data. Therefore, one can predict the boundary of reservoir in which hydrocarbon exists. B. Baygun et. al (1985) used fuzzy logic as classifier for delineation of geological objects in a mature hydrocarbon reservoir with many wells. B. Baygun et. al have shown that fuzzy logic can be used to extract dimensions and orientation of geological bodies and the geologist can use such a technique for reservoir characterization in a very quick way through bypassing several tedious steps. H. C. Chen et al. in their study used fuzzy set theory as fuzzy regression analysis for extraction of parameter for Archie equation. Bezdek et. al (1981) also reported a series of the applications of fuzzy sets theory in geostatical analysis. Tamhane et al (2002,) show how to integrate linguistic descriptions in petroleum reservoirs using fuzzy logic.

Many of our geophysical analysis techniques such as migration, DMO, wave equation modeling as well as the potential methods (gravity, magnetic, electrical methods) use conventional partial differential wave equations with deterministic coefficients. The same is true for the partial differential equations used in reservoir simulation. For many practical and physical reasons deterministic parameters for the coefficients of these PDEs leads unrealistic (for example medium velocities for seismic wave propagation or fluid flow for Darcy equation). Stochastic parameters in theses cases can provide us with a more practical characterization. Fuzzy coefficients for PDEs can prove to be even more realistic and easy to parameterize. Today's deterministic processing and interpretation ideas will give way to stochastic methods, even if the industry has to rewrite the book on geophysics. That is, using wave equations with random and fuzzy coefficients to describe subsurface velocities and densities in statistical and membership grade terms, thereby enabling a better description of wave propagation in the subsurface–particularly when a substantial amount of heterogeneity is present. More generalized applications of geostatistical techniques will emerge, making it possible to introduce risk and uncertainty at the early stages of the seismic data processing and interpretation loop.

5 Neuro-Fuzzy Techniques

In recent years, considerable attention has been devoted to the use of hybrid neural-network/fuzzy-logic approaches as an alternative for pattern recognition, clustering, and statistical and mathematical modeling. It has been shown that neural network models can be used to construct internal models that recognize fuzzy rules.

Neuro-fuzzy modeling is a technique for describing the behavior of a system using fuzzy inference rules within a neural network structure. The model has a unique feature in that it can express linguistically the characteristics of a complex nonlinear system. As a part of any future research opportunities, we will use the neuro-fuzzy model originally presented by Sugeno and Yasukawa (1993). The neuro-fuzzy model is characterized by a set of rules. The rules are expressed as follows:

R^i : if x_1 is A_1^i and x_2 is A_2^i ... and x_n is A_n^i (Antecedent) [1]

then $y^* = f_i(x_1, x_2, \ldots, x_n)$ (Consequent)

where $f_i(x_1, x_2, \ldots, x_n)$ can be constant, linear, or a fuzzy set.

For the linear case: $f_i(x_1, x_2, \ldots, x_n) = a_{i0} + a_{i1} x_1 + a_{i2} x_2 + \ldots + a_{in} x_n$ [2]

Therefore, the predicted value for output y is given by:

$$y = \Sigma_i \mu_i f_i(x_1, x_2, \ldots, x_n) / \Sigma \mu_i \quad [3]$$

with

$$\mu_i = \Pi_j A_j^i (x_j) \quad [4]$$

where R_i is the ith rule, x_j are input variables, y is output, A_j^i are fuzzy membership functions (fuzzy variables), a_{ij} constant values.

As a part of any future research opportunities, we will use the Adaptive Neuro-Fuzzy Inference System (ANFIS) technique originally presented by Jang (1992). The model uses neuro-adaptive learning techniques, which are similar to those of neural networks. Given an input/output data set, the ANFIS can construct a fuzzy inference system (FIS) whose membership function parameters are adjusted using the back-propagation algorithm or other similar optimization techniques. This allows fuzzy systems to learn from the data they are modeling.

5.1 Neural-fuzzy model for rule extraction

In this section, a neuro-fuzzy model will be developed for model identification and knowledge extraction (rule extraction) purposes. The model is characterized by a set of rules which can be further used for representation of data in the form of linguistic variables. Therefore, in this situation the fuzzy variables become linguistic variables. The neuro-fuzzy technique is used to implicitly cluster the data while finding the nonlinear mapping. The neuro-fuzzy model developed in this study is an approximate fuzzy model with triangular and Gaussian membership functions originally presented by Sugeno and Yasukawa (1993). K-Mean technique is used for clustering and the network is trained using a backpropagation algorithm and modified Levenberge-Marquardt optimization technique.

In this study, the effect of rock parameters and seismic attenuation on permeability will be analyzed based on soft computing techniques and experimental data. The software will use fuzzy logic techniques because the data and our requirements are imperfect. In addition, it will use neural network techniques, since the functional structure of the data is unknown. In particular, the software will be used to group data into important data sets; extract and classify dominant and interesting patterns that exist between these data sets; and discover secondary, tertiary and higher-order data patterns. The objective of this section is to predict the permeability based on grain size, clay content, porosity, P-wave velocity, and P-wave attenuation.

5.2 Prediction of permeability based on porosity, grain size, clay content, P-wave velocity, and P-wave attenuation.

In this section, a neural-fuzzy model will be developed for nonlinear mapping and rule extraction (knowledge extraction) between porosity, grain size, clay content, P-wave velocity, P-wave attenuation and permeability. **Figure 12** shows typical data, which has been used in this study. In this study, permeability will be predicted based on the following rules and equations. (1) through (4):

IF Rock Type= Sandstones
[5]
AND Porosity=[p1,p2]
AND Grain Size =[g1,g2]
AND Clay Content =[c1,c2]
AND P-Wave Vel.=[pwv1,pwv2]
AND P-Wave Att.=[pwa1,pwa2]
THEN Y*= a0+a1*P+a2*G+a3*C+a4*PWV+a5*PWA.

Where, P is %porosity, G is grain size, C is clay content, PWV is P-wave velocity, and P-wave attenuation, Y*, is equivalent to f in equation 1.

Data are scaled uniformly between -1 and 1 and the result is given in the scaled domain. The available data were divided into three data sets: training, testing, and validation. The neuro-fuzzy model was trained based on a training data set and continuously tested using a test data set during the training phase. Training

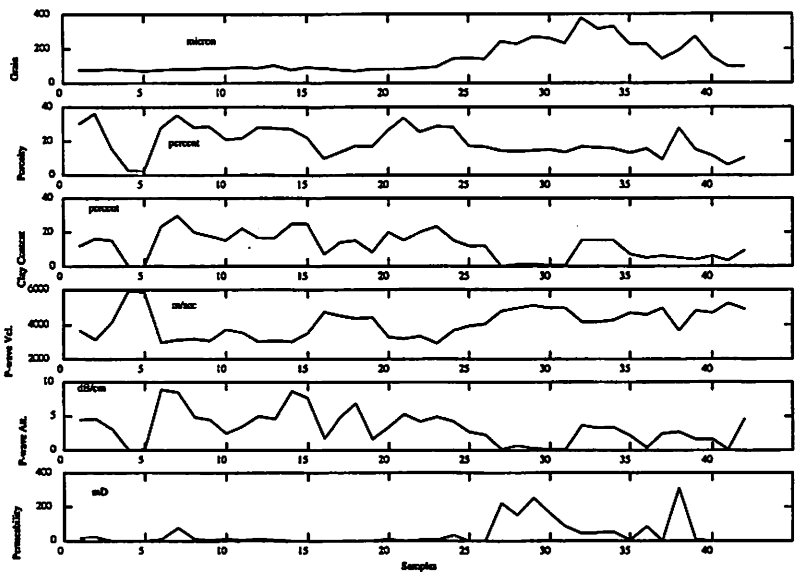


Figure 12. Actual data (Boadu 1997).

was stopped when it was found that the model's prediction suffered upon continued training. Next, the number of rules was increased by one and training was repeated. Using this technique, an optimal number of rules were selected. **Figures 13A** through **13E** and **Table 5** show typical rules extracted from the data. In **Table 1**, Column 1 through 5 show the membership functions for porosity, grain size, clay content, P-wave velocity, and P-wave attenuation respectively. Using the model defined by equations 1 through 4 and membership functions defined in **Figures 13A** through **13E** and **Table 5**, permeability was predicted as shown in **Figure 14A**. In this study, 7 rules were identified for prediction of permeability based on porosity, grain size, clay content, P-wave velocity, and P-wave attenuation (**Figures 13A** through **13E** and **Figure 14A**). In addition, 8 rules were identified for prediction of permeability based on porosity, clay content, P-wave velocity, and P-wave attenuation (**Figure 14B**). Ten rules were identified for prediction of permeability based on porosity, P-wave velocity, and P-wave attenuation (**Figure 14C**). Finally, 6 rules were identified for prediction of permeability based on grain size, clay content, P-wave velocity, and P-wave attenuation (**Figure 14D**). The neural network model shows very good performance for prediction of permeability. In this situation, not only a nonlinear mapping and relationship was identified between porosity, grain size, clay content, P-wave velocity, and P-wave attenuation, and permeability, but the rules existing between data were also

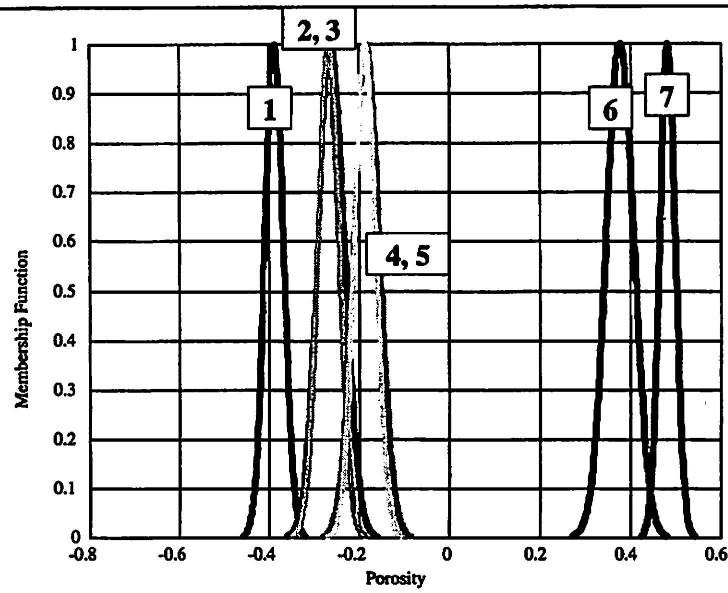


Figure 13A. Typical rules extracted from data, 7 Rules (Porosity).

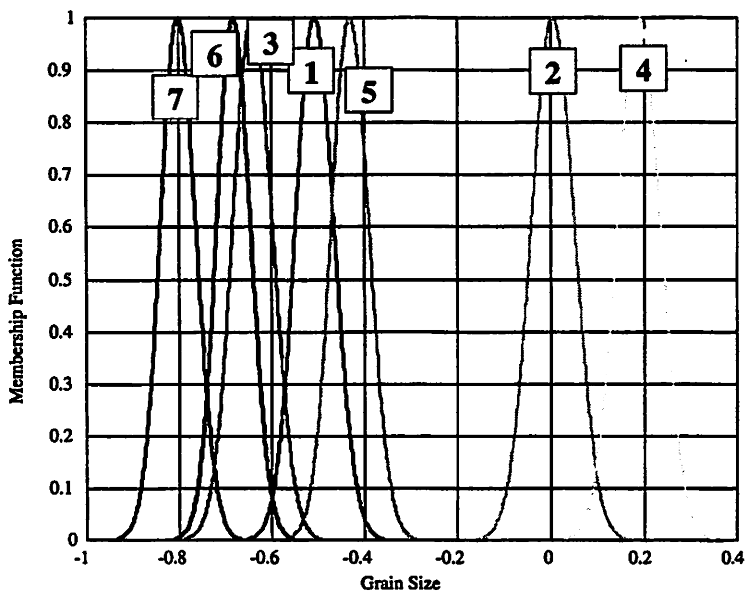


Figure 13B. Typical rules extracted from data, 7 Rules (Grain Size).

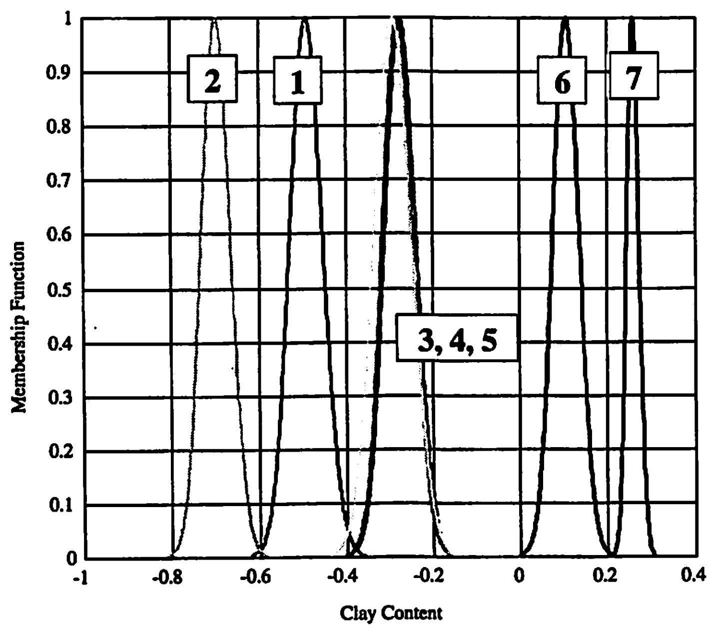


Figure 13C. Typical rules extracted from data, 7 Rules (Clay Content).

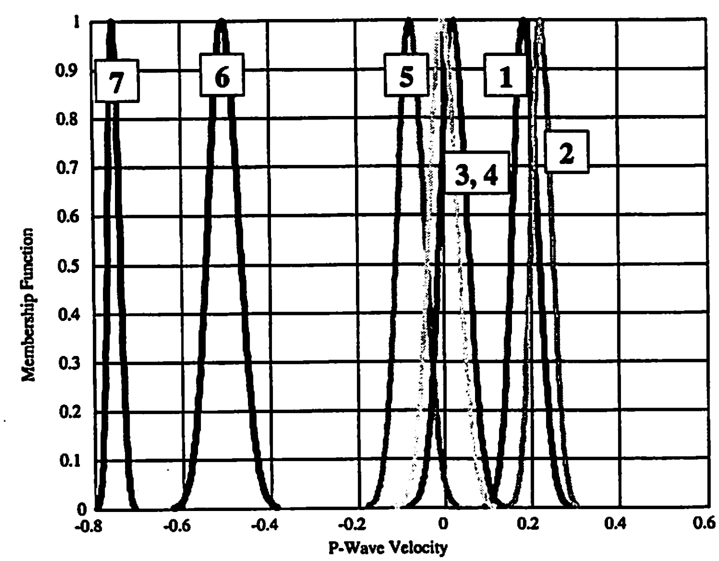


Figure 13D. Typical rules extracted from data, 7 Rules (P-Wave Velocity).

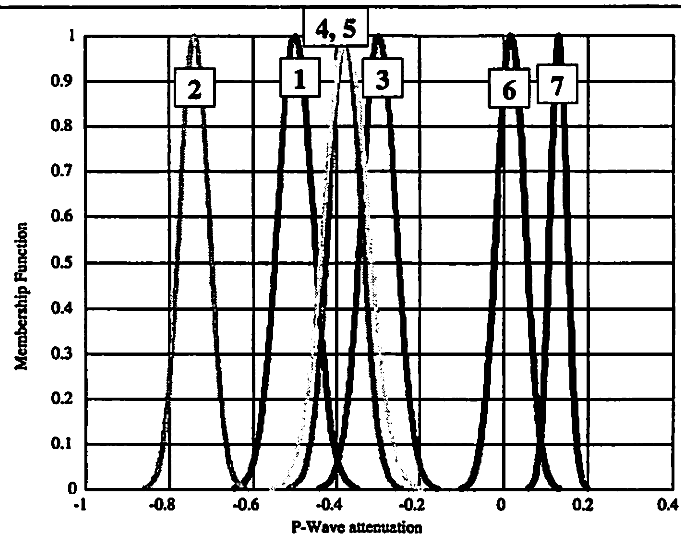


Figure 13E. Typical rules extracted from data, 7 Rules (P-Wave Attenuation).

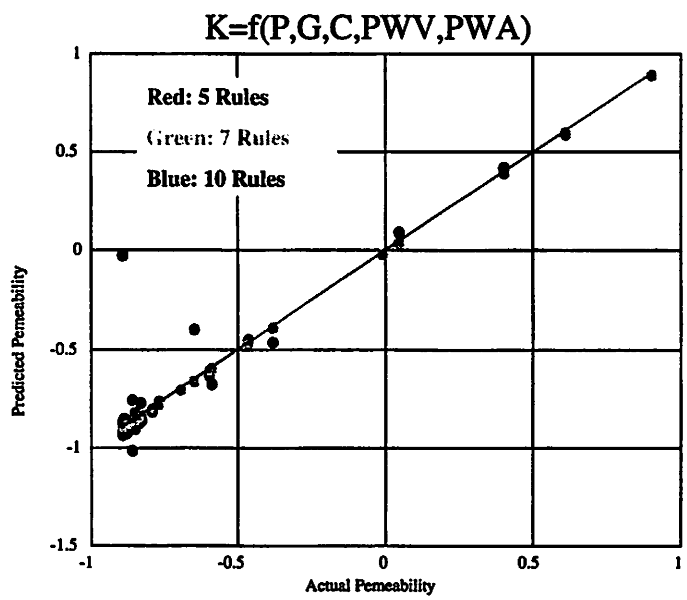


Figure 14A. Performance of Neural-Fuzzy model for prediction of permeability [K= f (P, G, C, PWV, PWA)].

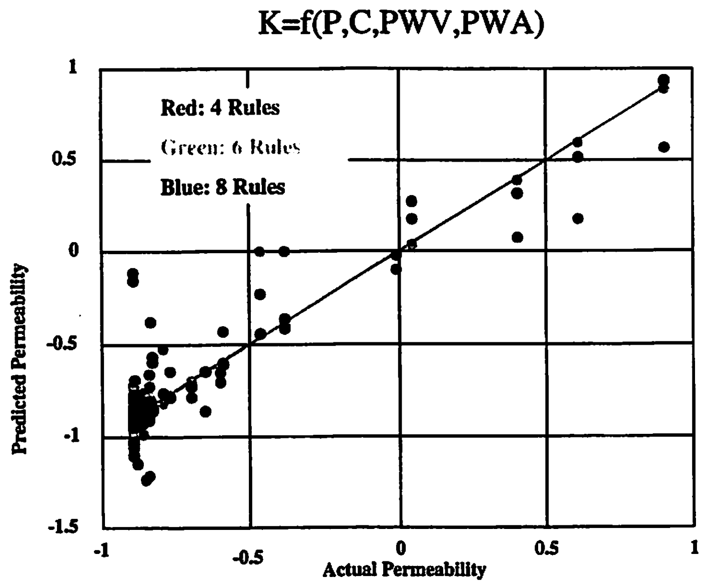


Figure 14B. Performance of Neural-Fuzzy model for prediction of permeability [K= f (P, C, PWV, PWA)].

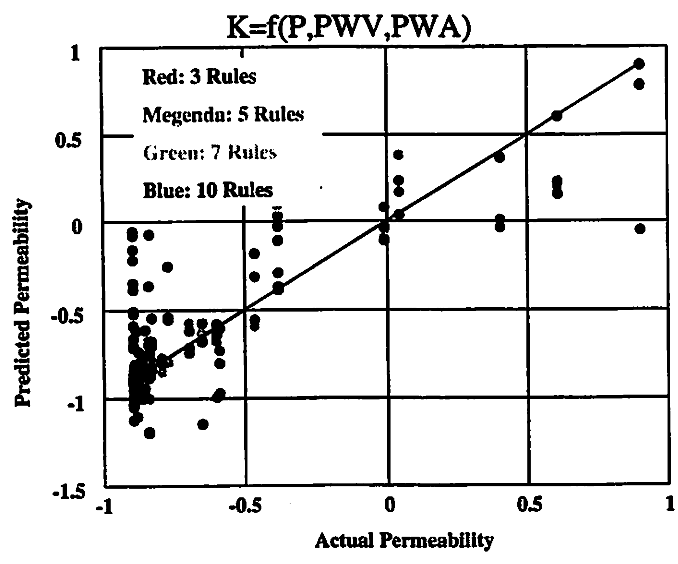


Figure 14C. Performance of Neural-Fuzzy model for prediction of permeability [K= f (P, PWV, PWA)].

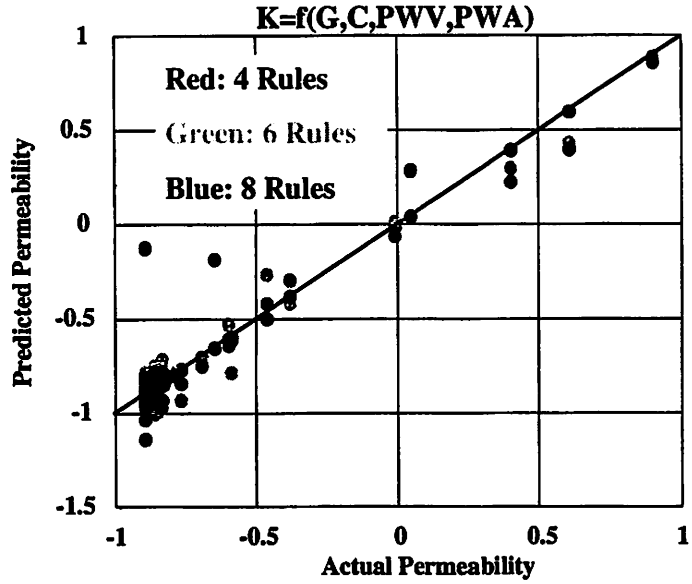


Figure 14D. Performance of Neural-Fuzzy model for prediction of permeability [K= f (G, C, PWV, PWA)].

Table 5. Boundary of rules extracted from data.

Porosity	Grain Size	Clay Content	P_Wave Velocity	P_Wave Attenuation
[-0.4585, -0.3170]	[-0.6501, -0.3604]	[-0.6198, -0.3605]	[0.0893, 0.2830]	[-0.6460 -0.3480]
[0.4208, 0.5415]	[-0.9351, -0.6673]	[0.2101, 0.3068]	[-0.7981, -0.7094]	[0.0572 0.2008]
[-0.3610, -0.1599]	[-0.7866, -0.4923]	[-0.3965, -0.1535]	[-0.0850, 0.1302]	[-0.4406 -0.1571]
[-0.2793, -0.0850]	[-0.5670, -0.2908]	[-0.4005, -0.1613]	[-0.1801, 0.0290]	[-0.5113 -0.2439]
[-0.3472, -0.1856]	[-0.1558, 0.1629]	[-0.8093, -0.5850]	[0.1447, 0.3037]	[-0.8610 -0.6173]
[0.2700, 0.4811]	[-0.8077, -0.5538]	[-0.0001, 0.2087]	[-0.6217, -0.3860]	[-0.1003 0.1316]
[-0.2657, -0.1061]	[0.0274, 0.3488]	[-0.4389, -0.1468]	[-0.1138, 0.1105]	[-0.5570 -0.1945]

identified. For this case study, our software clustered the parameters as grain size, P-wave velocity/porosity (as confirmed by **Figure 15** since a clear linear relationship exists between these two variables), and P-wave attenuation/clay content (as it is confirmed by **Figure 16** since an approximate linear relationship exists between these two variables). In addition, using the rules extracted, it was shown that P-wave velocity is closely related to porosity and P-wave attenuation is closely related to clay content. Boadu (1997) also indicated that the most influential rock parameter on the attenuation is the clay content. In addition our software ranked the variables in the order grain size, p-wave velocity, p-wave attenuation and clay content/porosity (since clay content and porosity can be predicted from p-wave velocity and p-wave attenuation).

6 Genetic Algorithms

Evolutionary computing represents computing with the use of some known mechanisms of evolution as key elements in algorithmic design and implementation. A variety of algorithms have been proposed. They all share a common conceptual base of simulating the evolution of individual structures via processes of parent selection, mutation, crossover and reproduction. The major one is the genetic algorithms (GAs) (Holland, 1975).

Genetic algorithm (GA) is one of the stochastic optimization methods which is simulating the process of natural evolution. GA follows the same principles as those in nature (survival of the fittest, Charles Darwin). GA first was presented by John Holland as an academic research. However, today GA turn out to be one of the most promising approaches for dealing with complex systems which at first nobody could imagine that from a relative modest technique. GA is applicable to multi-objectives optimization and can handle conflicts among objectives. Therefore, it is robust where multiple solution exist. In addition, it is highly efficient and it is easy to use.

Another important feature of GA is its ability to extract knowledge in terms of fuzzy rules. GA is now widely used and applied to discovery of fuzzy rules. However, when the data sets are very large, it is not easy to extract the rules. To overcome such a limitation, a new coding technique has been presented recently. The new coding method is based on biological DNA. The DNA coding method and the mechanism of development from artificial DNA are suitable for knowledge extraction from large data set. The DNA can have many redundant parts which is important for extraction of knowledge. In addition, this technique allows overlapped representation of genes and it has no constraint on crossover points. Also, the same type of mutation can be applied to every locus. In this technique, the length of chromosome is variable and it is easy to insert and/or delete any part

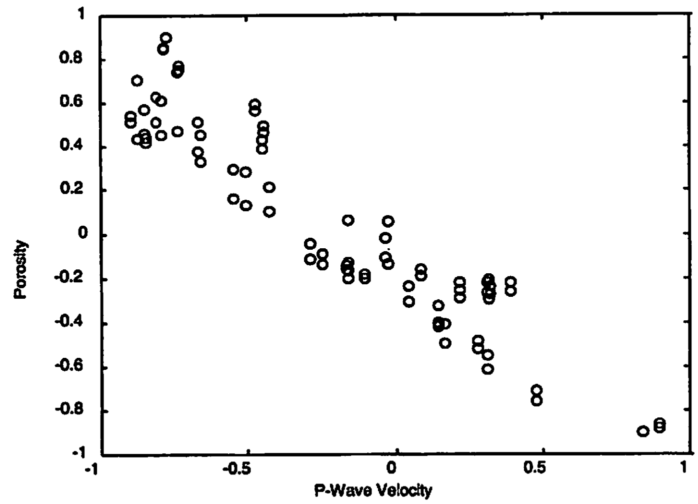


Figure 15. Relationship between P-Wave Velocity and Porosity.

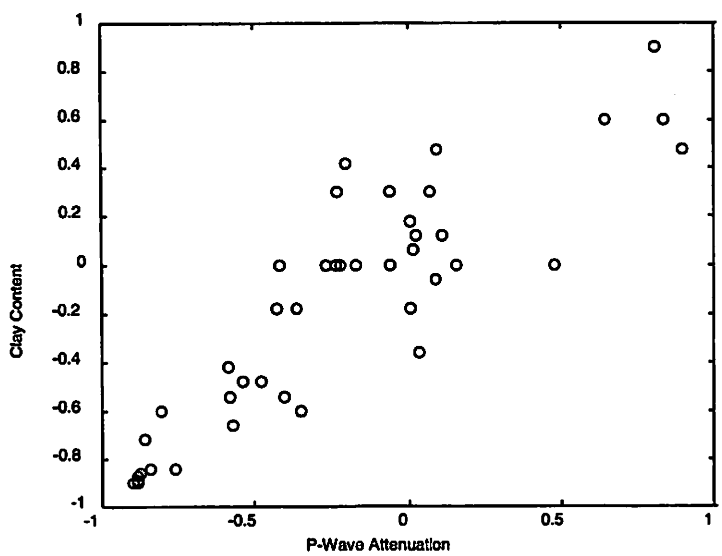


Figure 16. Relationship between P-Wave Attenuation and Clay Content.

of DNA. Today, genetic algorithm can be used in a hierarchical fuzzy model for pattern extraction and to reduce the complexity of the neuro-fuzzy models. In addition, GA can be use to extract the number of the membership functions required for each parameter and input variables, and for robust optimization along the multidimensional, highly nonlinear and non-convex search hyper-surfaces.

GAs work by firstly encoding the parameters of a given estimator as chromosomes (binary or floating-point). This is followed by populating a range of potential solutions. Each chromosome is evaluated by a fitness function. The better parent solutions are reproduced and the next generation of solutions (children) is generated by applying the genetic operators (crossover and mutation). The children solutions are evaluated and the whole cycle repeats until the best solution is obtained.

The methodology is in fact general and can be applied to optimizing parameters in other soft computing techniques, such as neural networks. In Yao (1999), the author gave an extensive review of the use of evolutionary computing in neural networks with more than 300 references. Three general areas are: evolution of connection weights; evolution of neural network architectures; and evolution of learning rules.

Most geoscience applications began in early 1990s. Gallagher and Sambridge (1994) presented an excellent overview on the use of GAs in seismology. Other applications include geochemical analysis, well logging and seismic interpretation.

Fang et al. first used GAs to predict porosity and permeability from compositional and textural information and the Archie parameters in petrophysics. The same authors later used the same method to map geochemical data into a rock's mineral composition (1996). The performance was much better than the results obtained from linear regression and nonlinear least-squares methods.

In Huang et al.(1998), the authors used GAs to optimize the connection weights in a neural network for permeability prediction from well logs. The study showed that the GA-trained networks (neural-genetic model) gave consistently smaller errors compared to the networks trained by the conventional gradient descent algorithm (backpropagation). However, GAs were comparatively slow in convergence. In Huang et al.(2000), the same authors initialized the connection weights in GAs using the weights trained by backpropagation. The technique was also integrated with fuzzy reasoning, which gave a hybrid system of neural-fuzzy-genetic (Huang, 1998). This improved the speed of convergence and still obtained better results.

Another important feature of GAs is its capability of extracting fuzzy rules. However, this becomes unpractical when the data sets are large in size. To overcome this, a new encoding technique has been presented recently, which is based on the understanding of biological DNA. Unlike the conventional chromosomes, the length of chromosome is variable and it is flexible to insert new parts and/or delete redundant parts. In Yashikawa et al. (1998) and Nikravesh et al.(1998), the authors used a hybrid system of neural-fuzzy-DNA model for knowledge extraction from seismic data, mapping the well logs into seismic data and reconstruction of porosity based on multi-attributes seismic mapping.

6.1 Geoscience Applications of Genetic Algorithms

Most of the applications of the GA in the area of petroleum reservoir or in the area of geoscience are limited to inversion techniques or used as optimization technique. While in other filed, GA is used as a powerful tool for extraction of knowledge, fuzzy rules, fuzzy membership, and in combination with neural network and fuzzy-logic. Recently, Nikravesh et. al, (?) proposed to use a neuro-fuzzy-genetic model for data mining and fusion in the area of geoscience and petroleum reservoirs. In addition, it has been proposed to use neuro-fuzzy-DNA model for extraction of knowledge from seismic data and mapping the wireline logs into seismic data and reconstruction of porosity (and permeability if reliable data exist for permeability) based on multi-attributes seismic mapping. Seismic inversion was accomplished using genetic algorithms by Mallick (1999). Potter et al (1999) used GA for stratigraphic analysis. For an overview of GA in exploration problems see McCormack et al (1999)

7 Principal Component Analysis and Wavelet

Some of the data Fusion and data mining methods used in exploration applications are as follows.

First we need to reduce the space to make the data size more manageable as well as reducing the time required for data processing. We can use Principal Component Analysis. Using the eigen value and vectors, we can reduce the space domain. We choose the eigenvector corresponding to the largest eigenvalues. Then in the eigenvector space we use Fuzzy K-Mean or Fuzzy C-Mean technique. For details of Fuzzy C-Means algorithm see Cannon et al (1986). Also, see Lashgari (1991), Aminzadedh (1989) and Aminzadeh (1994) for the application of Fuzzy Logic and Fuzzy K-Means algorithm in several earth exploration problems.

We can also use Wavelet and extract the patterns and Wavelets describing different geological settings and the respective rock properties. Using the Wavelet and neural network, we can fuse the data for nonlinear modeling. For clustering purposes, we can use the output from Wavelet and use Fuzzy C-Mean or Fuzzy K-Mean. To use uncertainty and see the effect of the uncertainty, it is easy to add the distribution to each point or some weight for importance of the data points. Once we assign some weight to each point, then we can correspond each weight to number of points in a volume around each point.

Of course the techniques based on principal component analysis has certain limitations. One of the limitations is when SNR is negative or zero causing the technique to fail. The reason for this is the singularity of the variance and covariance matrices. Therefore, an important step is to use KF or some sort of Fuzzy set theory for noise reduction and extraction of Signal.

8 Intelligent Reservoir Characterization

In reservoir engineering, it is important to characterize how 3-D seismic information is related to production, lithology, geology, and logs (e.g. porosity, density, gamma ray, etc.) (Boadu 1997; Nikravesh 1998a-b; Nikravesh et al., 1998; Chawathe et al. 1997; Yoshioka et al 1996; Schuelke et al. 1997; Monson and Pita 1997, Aminzadeh and Chatterjee, 1985). Knowledge of 3-D seismic data will help to reconstruct the 3-D volume of relevant reservoir information away from the well bore. However, data from well logs and 3-D seismic attributes are often difficult to analyze because of their complexity and our limited ability to understand and use the intensive information content of these data. Unfortunately, only linear and simple nonlinear information can be extracted from these data by standard statistical methods such as ordinary Least Squares, Partial Least Squares, and nonlinear Quadratic Partial Least-Squares. However, if *a priori* information regarding nonlinear input-output mapping is available, these methods become more useful.

Simple mathematical models may become inaccurate because several assumptions are made to simplify the models in order to solve the problem. On the other hand, complex models may become inaccurate if additional equations, involving a more or less approximate description of phenomena, are included. In most cases, these models require a number of parameters that are not physically measurable. Neural networks (Hecht-Nielsen 1989) and fuzzy logic (Zadeh 1965) offer a third alternative and have the potential to establish a model from nonlinear, complex, and multi-dimensional data. They have found wide application in analyzing experimental, industrial, and field data (Baldwin et al. 1990; Baldwin et al. 1989; Pezeshk et al. 1996; Rogers et al. 1992; Wong et al. 1995a, 1995b; Nikravesh et al. 1996; Nikravesh and Aminzadeh, 1997). In recent years, the utility of neural network and fuzzy logic analysis has stimulated growing interest among reservoir engineers, geologists, and geophysicists· (Nikravesh et al. 1998; Nikravesh 1998a; Nikravesh 1998b; Nikravesh and Aminzadeh 1998; Chawathe et al. 1997; Yoshika et al. 1996; Schuelke et al. 1997; Monson and Pita 1997; Boadu

1997; Klimentos and McCann 1990; Aminzadeh and Katz 1994). Boadu (1997) and Nikravesh et al. (1998) applied artificial neural networks and neuro-fuzzy successfully to find relationships between seismic data and rock properties of sandstone. In a recent study, Nikravesh and Aminzadeh (1999) used an artificial neural network to further analyze data published by Klimentos and McCann (1990) and analyzed by Boadu (1997). It was concluded that to find nonlinear relationships, a neural network model provides better performance than does a multiple linear regression model. Neural network, neuro-fuzzy, and knowledge-based models have been successfully used to model rock properties based on well log databases (Nikravesh, 1998b).

Monson and Pita (1997), Chawathe et al. (1997) and Nikravesh (1998b) applied artificial neural networks and neuro-fuzzy techniques successfully to find the relationships between 3-D seismic attributes and well logs and to extrapolate mapping away from the well bore to reconstruct log responses.

Adams et al. (1999a and 1999b), Levey et al. (1999), Nikravesh et al. (1999a and 1999b) showed schematically the flow of information and techniques to be used for intelligent reservoir characterization (IRESC) (**Figure 17**). The main goal will be to integrate soft data such as geological data with hard data such as 3-D seismic, production data, etc. to build a reservoir and stratigraphic model. Nikravesh et al. (1999a and 1999b) were developed a new integrated methodology to identify a nonlinear relationship and mapping between 3-D seismic data and production-log data and the technique was applied to a producing field. This advanced data analysis and interpretation methodology for 3-D seismic and production-log data uses conventional statistical techniques combined with modern soft-computing techniques. It can be used to predict: 1. mapping between production-log data and seismic data, 2. reservoir connectivity based on multi-attribute analysis, 3. pay zone recognition, and 4. optimum well placement (**Figure 18**). Three criteria have been used to select potential locations for infill drilling or recompletion (Nikravesh et al., 1999a and 1999b): 1. continuity of the selected cluster, 2. size and shape of the cluster, and 3. existence of high Production-Index values inside a selected cluster with high Cluster-Index values. Based on these criteria, locations of the new wells were selected, one with high continuity and potential for high production and one with low continuity and potential for low production. The neighboring wells that are already in production confirmed such a prediction (**Figure 18**).

Although these methodologies have limitations, the usefulness of the techniques will be for fast screening of production zones with reasonable accuracy. This new methodology, combined with techniques presented by Nikravesh (1998a, 1998b), Nikravesh and Aminzadeh (1999), and Nikravesh et al. (1998), can be used to reconstruct well logs such as DT, porosity, density, resistivity, etc. away from the well bore. By doing so, net-pay-zone thickness, reservoir models, and geological representations will be accurately identified. Accurate reservoir characterization through data integration is an essential step in reservoir modeling, management, and production optimization.

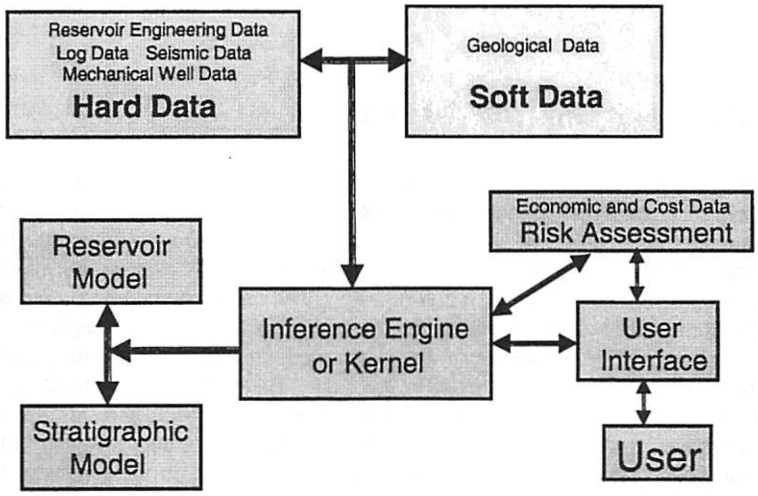


Figure 17. Integrated Reservoir Characterization (IRESC).

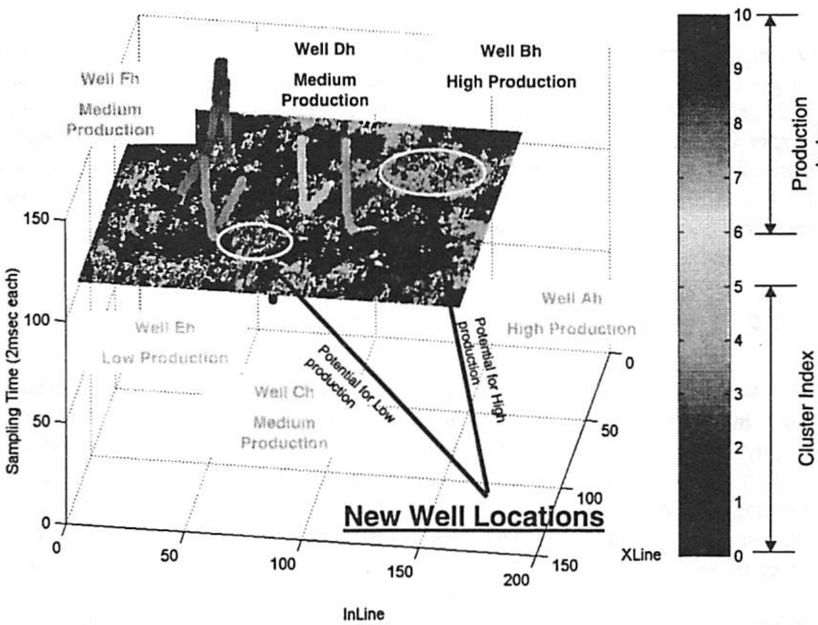


Figure 18. Optimal well placement (Nikravesh et al., 1999a and 1999b).

8.1 Reservoir Characterization

Figure 17 shows schematically the flow of information and techniques to be used for intelligent reservoir characterization (IRESC). The main goal is to integrate soft data such as geological data with hard data such as 3-D seismic, production data, etc. to build reservoir and stratigraphic models. In this case study, we analyzed 3-D seismic attributes to find similarity cubes and clusters using three different techniques: 1. k-means, 2. neural network (self-organizing map), and 3. fuzzy c-means. The clusters can be interpreted as lithofacies, homogeneous classes, or similar patterns that exist in the data. The relationship between each cluster and production-log data was recognized around the well bore and the results were used to reconstruct and extrapolate production-log data away from the well bore. The results from clustering were superimposed on the reconstructed production-log data and optimal locations to drill new wells were determined.

8.1.1 Examples

Our example are from fields that produce from the Ellenburger Group. The Ellenburger is one of the most prolific gas producers in the conterminous United States, with greater than 13 TCF of production from fields in west Texas. The Ellenburger Group was deposited on an Early Ordovician passive margin in shallow subtidal to intertidal environments. Reservoir description indicates the study area is affected by a karst-related, collapsed paleocave system that acts as the primary reservoir in the field studied (Adams et al., 1999; Levey et al., 1999).

8.1.2 Area 1

The 3-D seismic volume used for this study has 3,178,500 data points (**Table 6**). Two hundred, seventy-four well-log data points intersect the seismic traces. Eighty-nine production log data points are available for analysis (19 production and 70 non-production). A representative subset of the 3-D seismic cube, production log data, and an area of interest were selected in the training phase for clustering and mapping purposes. The subset (150 samples, with each sample equal to 2 msec of seismic data or approximately 20 feet of Ellenburger dolomite) was designed as a section (670 seismic traces) passing through all the wells as shown in **Figure 19** and has 100,500 (670*150) data points. However, only 34,170 (670*51) data points were selected for clustering purposes, representing the main

Ellenburger focus area. This subset covers the horizontal boreholes of producing wells, and starts approximately 15 samples (300 feet) above the Ellenburger, and

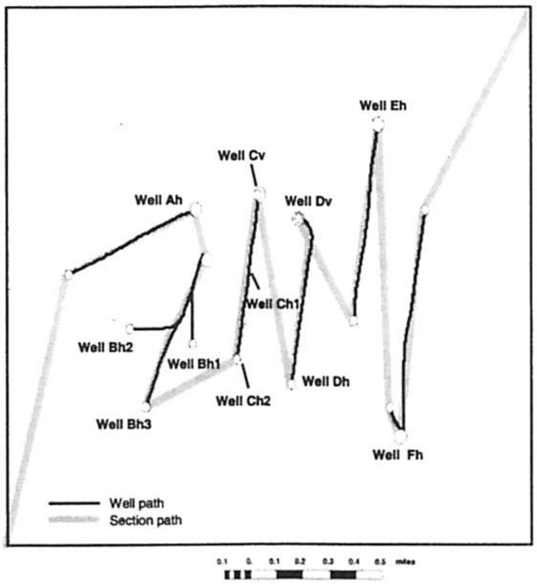


Figure 19. Seismic section passing through all the wells, Area 1.

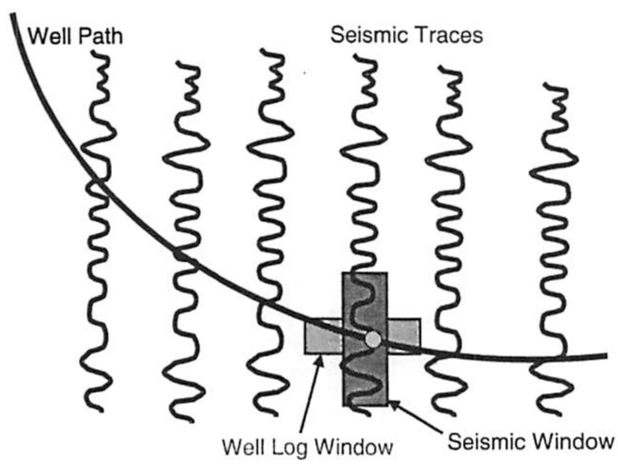


Figure 20. Schematic diagram of how the well path intersects the seismic traces.

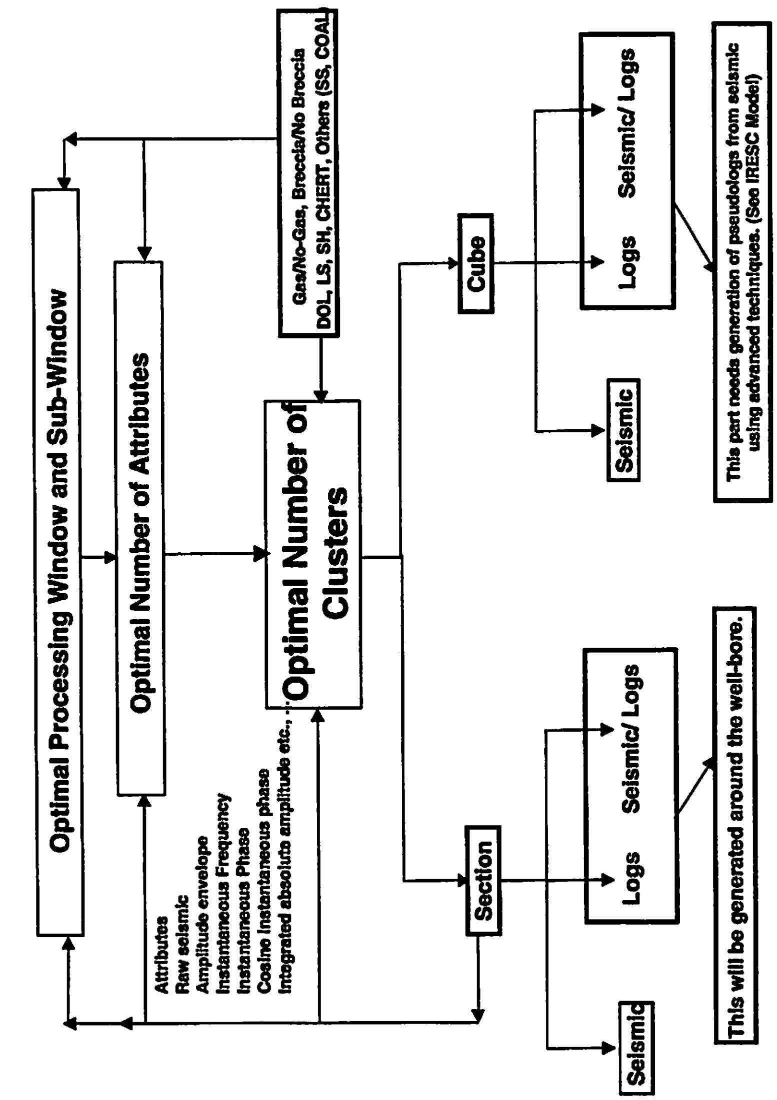


Figure 21. Iterative technique to select an optimal number of clusters, seismic attributes, and optimal processing windows.

Table 6. Typical statistics for main focus area, Area 1, and Ellenburger.

Data

Cube	Section
InLine: 163	Total Number of Traces: 670
Xline: 130	Time Sample: 150
Time Sample: 150	Total Number of Points: 100,500
Total Number of Points: 3,178,500	Used for Clustering: 34,170
	Section/Cube=%3.16
	For Clustering: %1.08

Well Data	Production Data
Total Number of Points: 274	Total Number of Points: 89
Well Data/Section: %0.80	Production: 19
Well Data/Cube:%0.009	No Production: 70
	Production Data/Section:%0.26
	Production Data/Cube:%0.003

Table 7. List of the attributes calculated in this study.

Attribute No.	abbrev.	Attribute
1.	ampenv	Amplitude Envelope
2.	ampwcp	Amplitude Weighted Cosine Phase
3.	ampwfr	Amplitude Weighted Frequency
4.	ampwph	Amplitude Weighted Phase
5.	aprpol	Apparent Polarity
6.	avgfre	Average Frequency
7.	cosiph	Cosine Instantaneous Phase
8.	deriamp	Derivative Instantaneous Amplitude
9.	deriv	Derivative
10.	domfre	Dominant Frequency
11.	insfre	Instantaneous Frequency
12.	inspha	Instantaneous Phase
13.	intaamp	Integrated Absolute Amplitude
14.	integ	Integrate
15.	raw	Raw Seismic
16.	sdinam	Second Derivative Instantaneous Amplitude
17.	secdev	Second Derivative

ends 20 samples (400 feet) below the locations of the horizontal wells. In addition, the horizontal wells are present in a 16-sample interval, for a total interval of 51 samples (102 msec or 1020 feet). **Table 6** shows typical statistics for this case study. **Figure 20** shows a schematic diagram of how the well path intersects the seismic traces. For clustering and mapping, there are two windows that must be optimized, the seismic window and the well log window. Optimal numbers of seismic attributes and clusters need to be determined, depending on the nature of the problem. **Figure 21** shows the iterative technique that has been used to select an optimal number of clusters, seismic attributes, and optimal processing windows for the seismic section shown in **Figure 19**. Expert knowledge regarding geological parameters has also been used to constrain the maximum number of clusters to be selected. In this study, six attributes have been selected (Raw Seismic, Instantaneous Amplitude, Instantaneous Phase, Cosine Instantaneous Phase, Instantaneous Frequency, and Integrate Absolute Amplitude) out of 17 attributes calculated (**Table 7**).

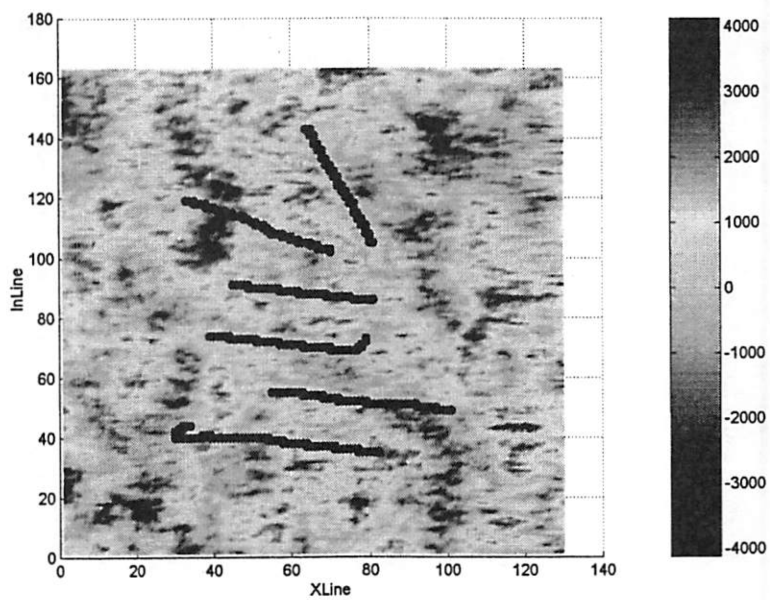


Figure 22. Typical time slice of Raw Seismic in Area 1 with Rule 1.

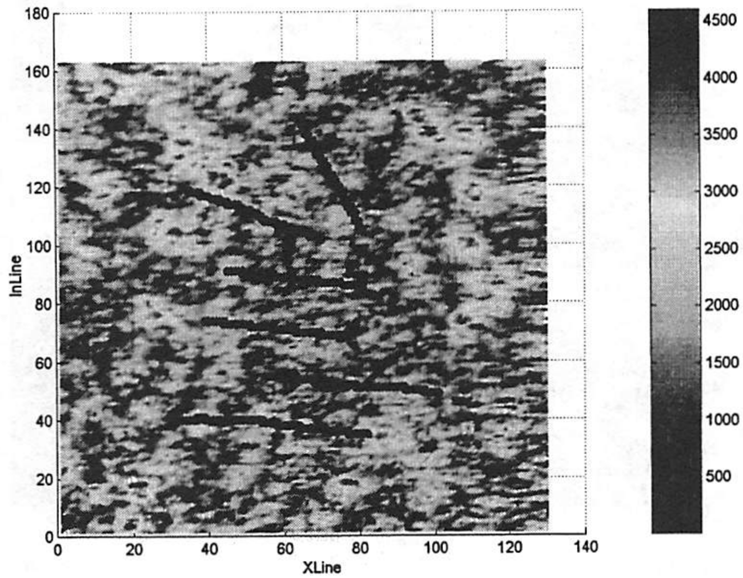


Figure 23. Typical time slice of Amplitude envelope in Area 1 with Rule 1.

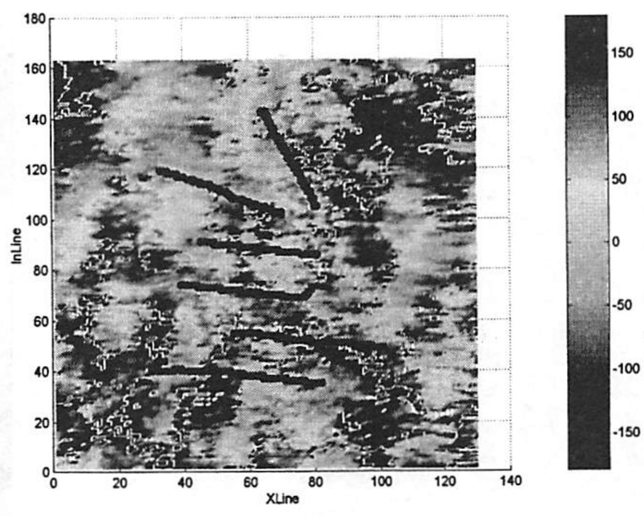


Figure 24. Typical time slice of Instantaneous Phase in Area 1 with Rule 1.

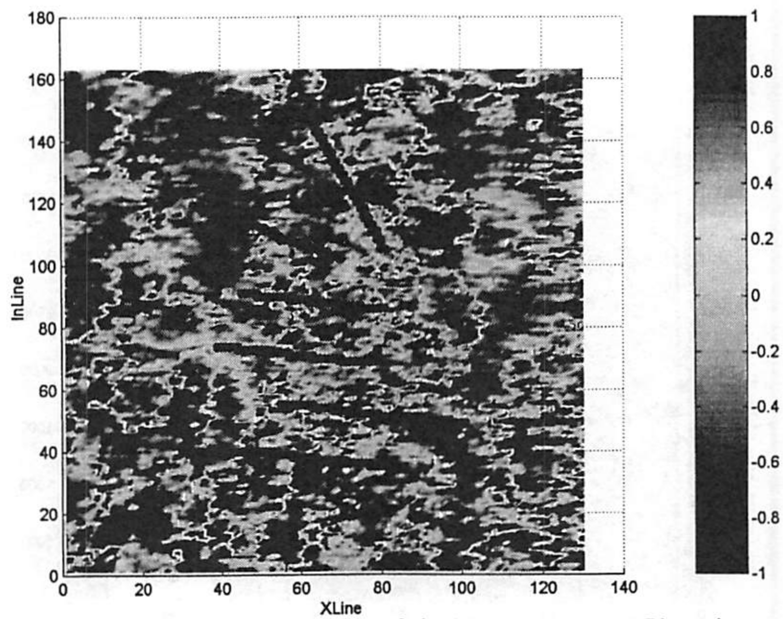


Figure 25. Typical time slice of Cosine Instantaneous Phase in Area 1 with Rule 1.

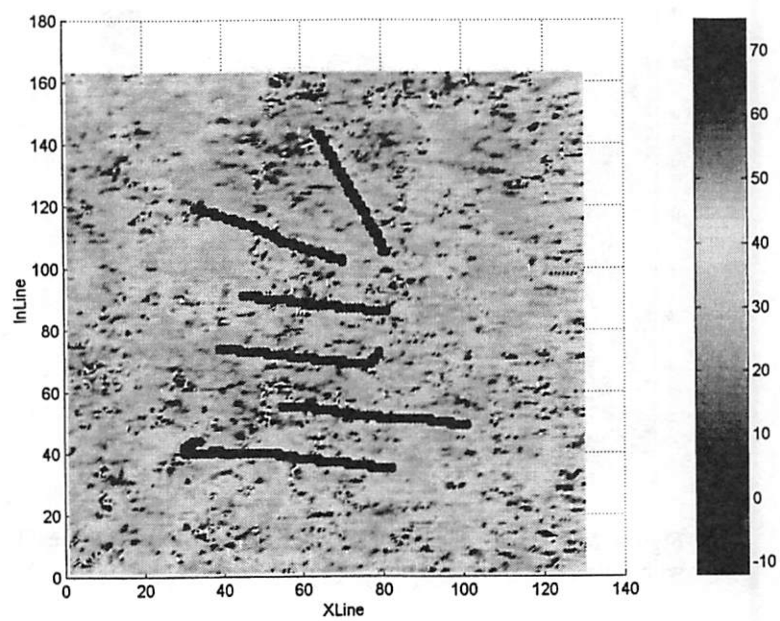


Figure 26. Typical time slice of Instantaneous Frequency in Area 1 with Rule 1.

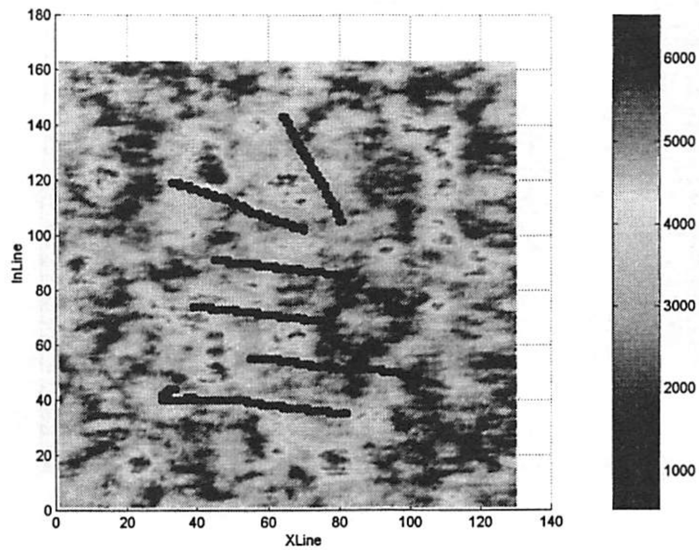


Figure 27. Typical time slice of Integrated Absolute Amplitude in Area 1 with Rule 1.

Figures 22 through **27** show typical representations of these attributes in our case study. Ten clusters were recognized, a window of one sample was used as the optimal window size for the seismic, and a window of three samples was used for the production log data. Based on qualitative analysis, specific clusters with the potential to be in producing zones were selected. Software was developed to do the qualitative analysis and run on a personal computer using Matlab™ software. **Figure 28** shows typical windows and parameters of this software. Clustering was based on three different techniques, k-means (statistical), neural network , and fuzzy c-means clustering. Different techniques recognized different cluster patterns as shown by the cluster distributions (**Figures 29A** through **31**). **Figures 29-31** through **14** show the distribution of clusters in the section passing through the wells as shown in **Figure 19**. By comparing k-mean (**Figure 12A**) and neural network clusters (**Figure 29**) with fuzzy clusters (**Figure 14**), one can conclude that the neural network predicted a different structure and patterns than did the other techniques. **Figures 29B and 29C** show a typical time-slice from the 3-D seismic cube that has been reconstructed with the extrapolated k-means cluster data. Finally, based on a qualitative analysis, specific clusters that have the potential to include producing zones were selected. Each clustering technique produced two clusters that included most of the production data. Each of these three pairs of clusters is equivalent.

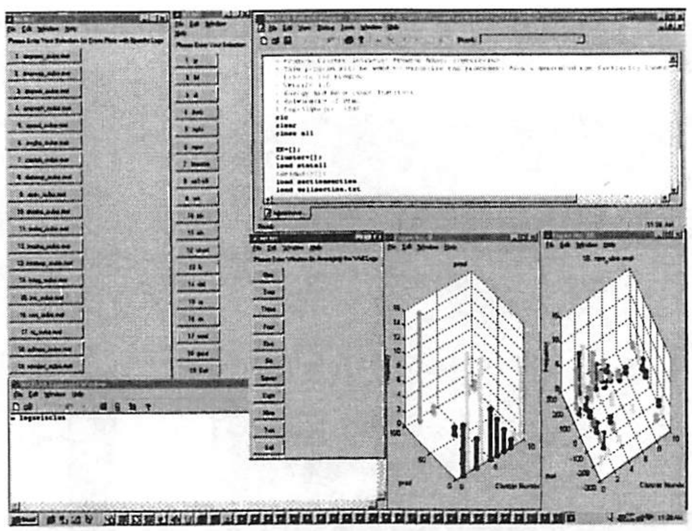


Figure 28. MatLab ™ software to do the qualitative analysis.

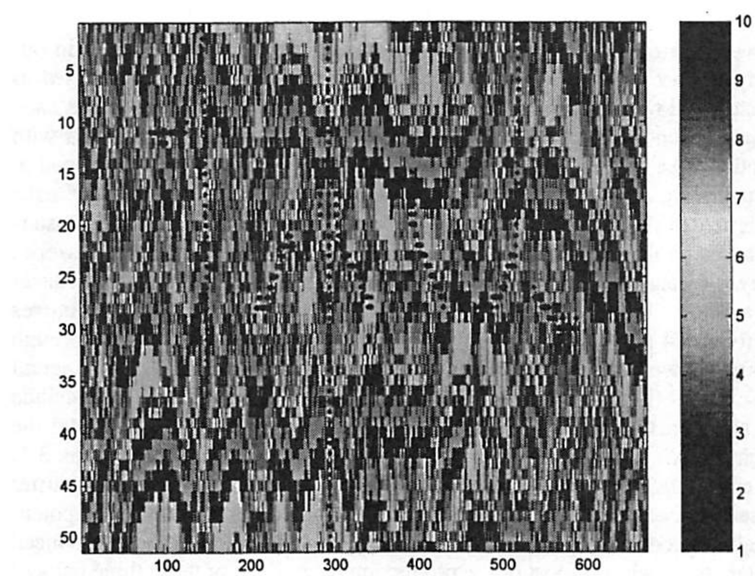


Figure 29A. Typical k-means distribution of clusters in the section passing through the wells as shown in Figure 19.

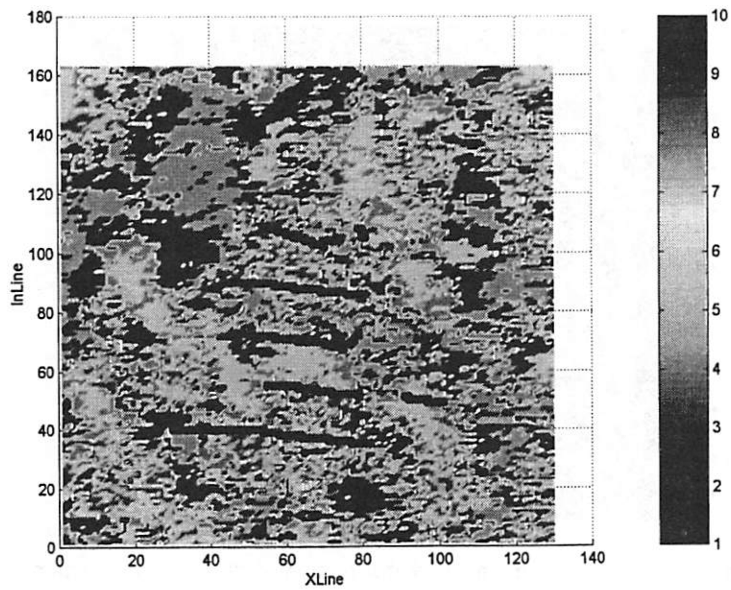


Figure 29B. Typical 2-D presentation of time-slice of k-means distribution of clusters.

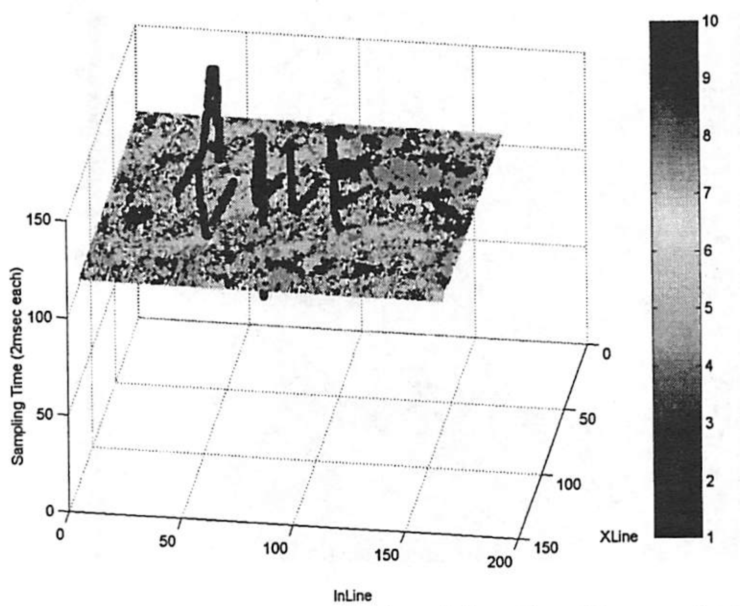


Figure 29C. Typical 3-D presentation of time-slice of k-means distribution of clusters.

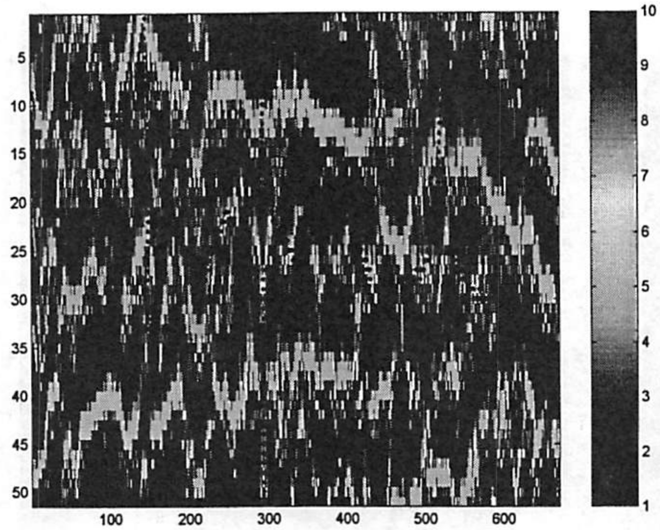


Figure 30. Typical neural network distribution of clusters in the section passing through the wells as shown in Figure 19.

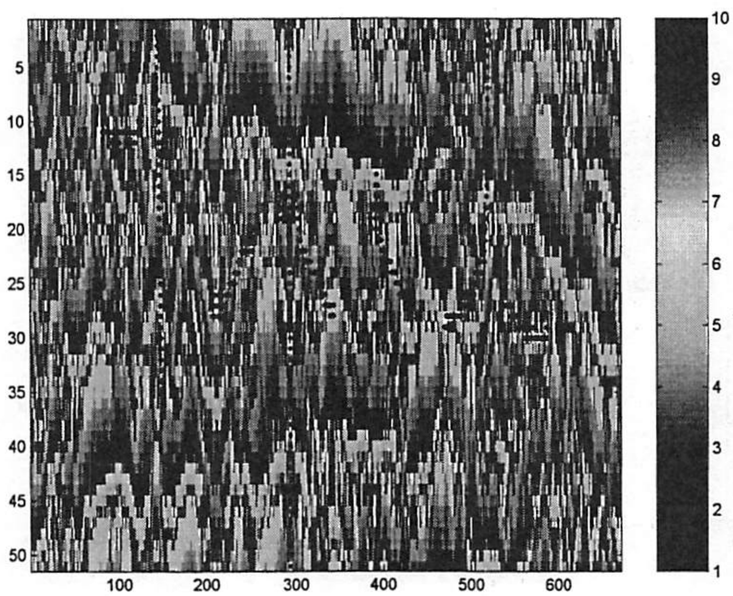


Figure 31. Typical fuzzy c-means distribution of clusters in the section passing through the wells as shown in Figure 19.

To confirm such a conclusion, cluster patterns were generated for the section passing through the wells as shown in **Figure 19**. **Figures 32 through 34** show the two clusters from each technique that correlate with production: clusters one and four from k-means clustering (**Figure 32**); clusters one and six from neural network clustering (**Figure 33**); and clusters six and ten from fuzzy c-means clustering (**Figure 34**). By comparing these three cross sections, one can conclude that, in the present study, all three techniques predicted the same pair of clusters based on the objective of predicting potential producing zones. However, this may not always be the case because information that can be extracted by the different techniques may be different. For example, clusters using classical techniques will have sharp boundaries whereas those generated using the fuzzy technique will have fuzzy boundaries.

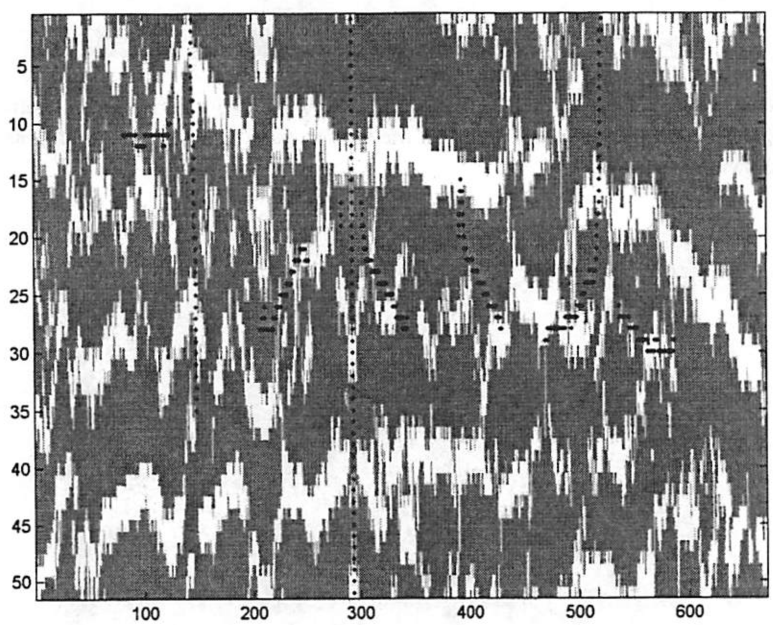


Figure 32. Clusters one and four that correlate with production using the k-means clustering technique on the section passing through the wells as shown in Figure 19.

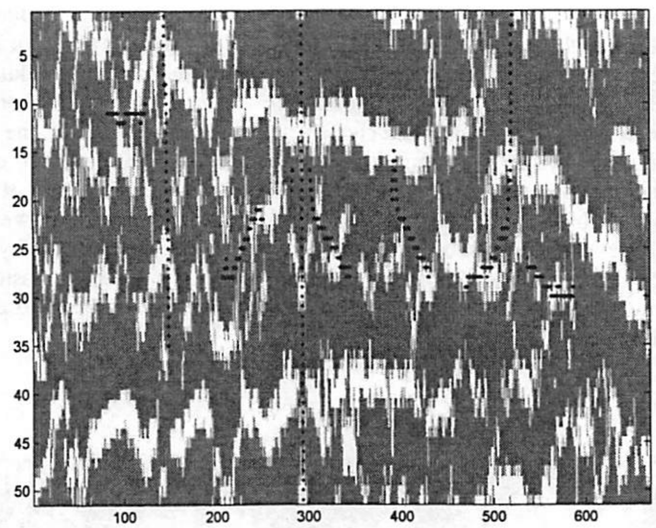


Figure 33. Clusters one and six that correlate with production using the neural network clustering technique on the section passing through the wells as shown in Figure 19.

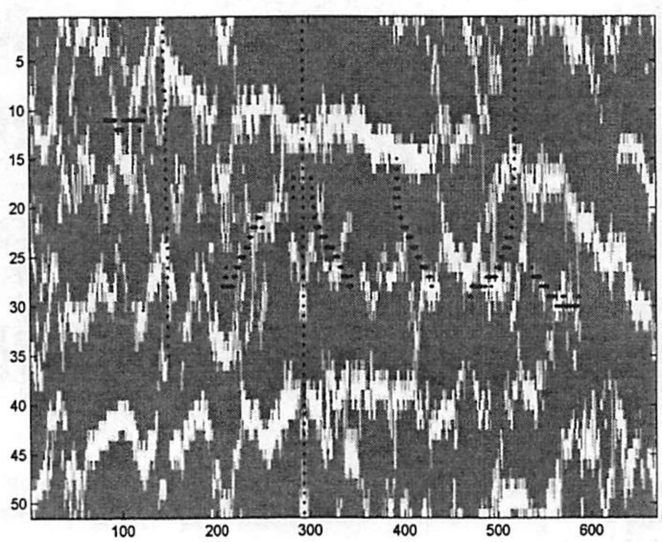


Figure 34. Clusters six and ten that correlate with production using the fuzzy c-means clustering technique on the section passing through the wells as shown in Figure 19.

Based on the clusters recognized in **Figures 32** through **34** and the production log data, a subset of the clusters has been selected and assigned as cluster 11 as shown in **Figures 35 and 36**. In this sub-cluster, the relationship between production-log data and clusters has been recognized and the production-log data has been reconstructed and extrapolated away from the well bore. Finally, the production-log data and the cluster data were superimposed at each point in the 3-D seismic cube. **Figures 37A and 37B (Figure 18)** show a typical time-slice of a 3-D seismic cube that has been reconstructed with the extrapolated production-log data and cluster data. The color scale in **Figures 37A and 20B** is divided into two indices, Cluster Index and Production Index. Criteria used to define Cluster Indices for each point are expressed as a series of dependent **IF-THEN** statements.

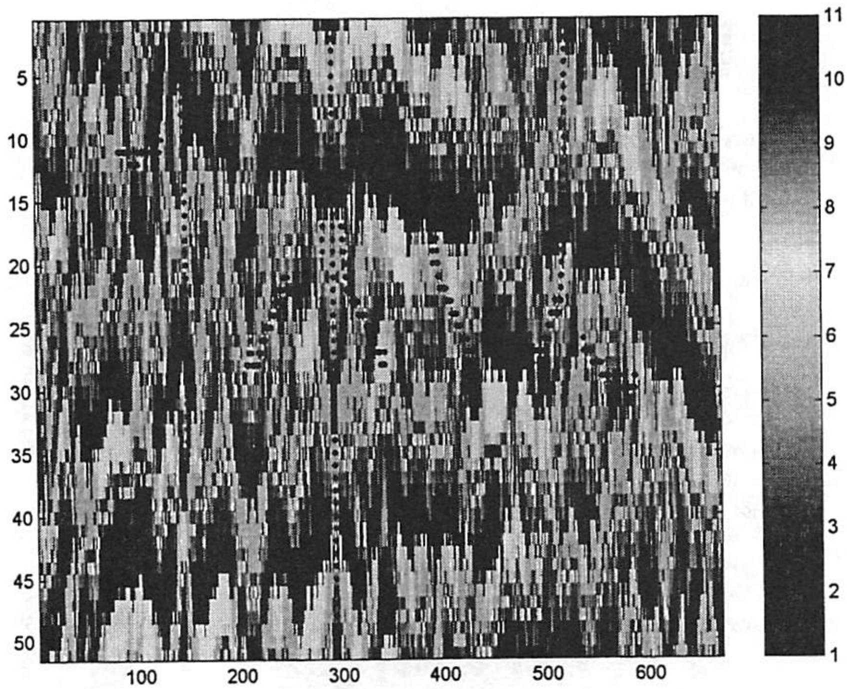


Figure 35. The section passing through all wells showing a typical distribution of clusters generated by combining the three sets of 10 clusters created by each clustering technique (k-means, neural network, and fuzzy c-means). Note that eleven clusters are displayed rather than the ten clusters originally generated. The eleventh cluster is a subset of the three pairs of clusters that contain most of the production.

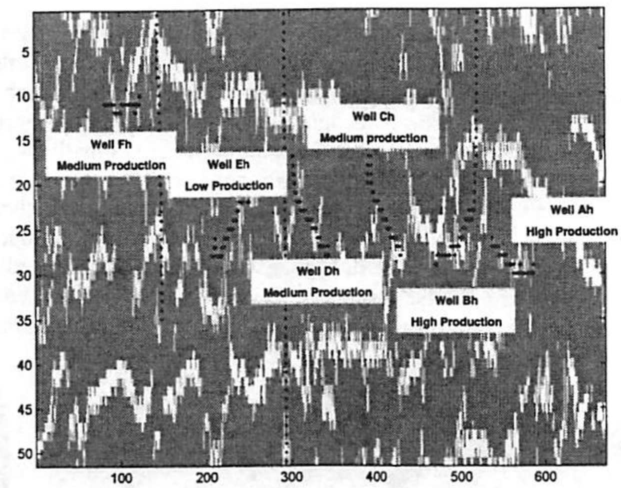


Figure 36. The section passing through all wells showing only the eleventh cluster, a subset of the three pairs of clusters that contains most of the production.

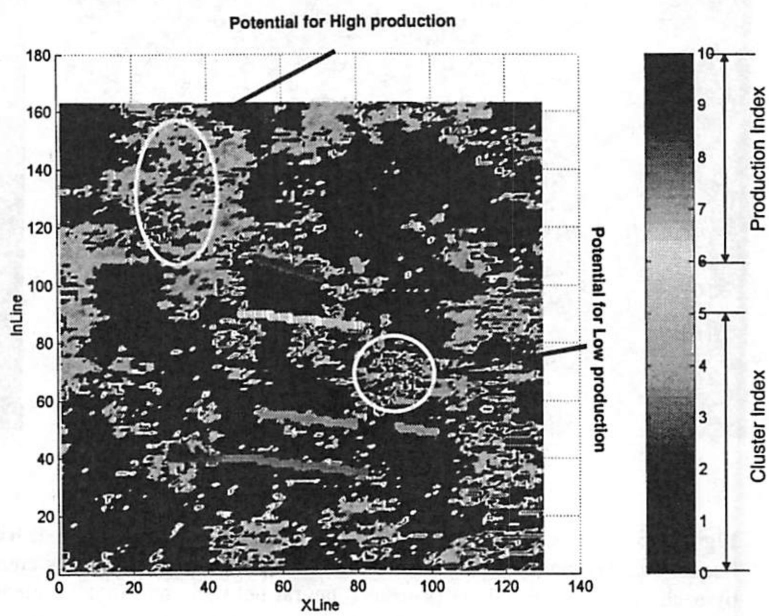


Figure 37A. A 2-D time slice showing clusters and production, with areas indicated for optimal well placement.

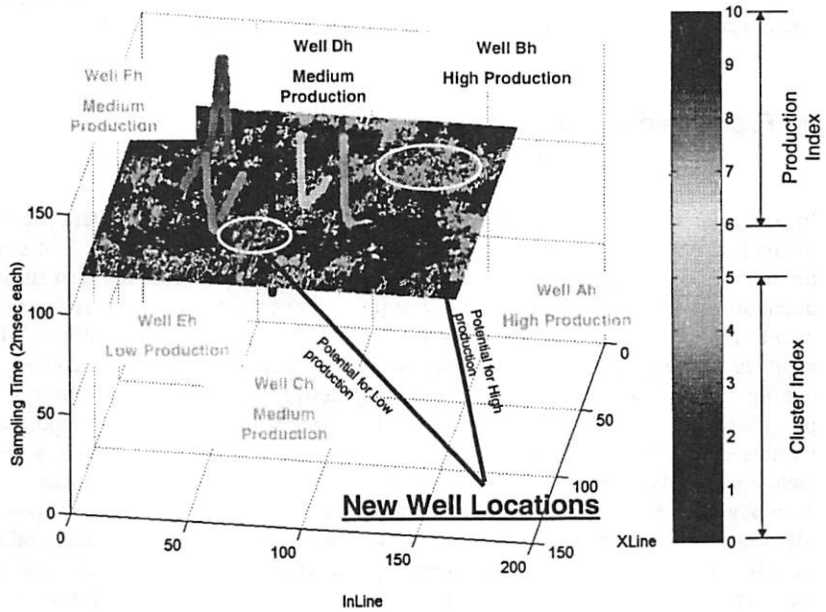


Figure 37B. An oblique view of the 2-D time slice in Figure 20A showing clusters and production, with areas indicated for optimal well placement.

Before defining Production Indices for each point within a specified cluster, a new cluster must first be defined based only on the seismic data that represents production-log data with averaged values greater than 0.50. Averaged values are determined by assigning a value to each sample of a horizontal borehole (two feet/sample). Sample intervals that are producing gas are assigned values of one and non-producing sample intervals are assigned values of zero. The optimum window size for production-log data is three samples and the averaged value at any point is the average of the samples in the surrounding window. After the new cluster is determined, a series of **IF-THEN** statements is used to define the Production Indices.

Three criteria have been used to select potential locations for infill drilling or recompletion: 1. continuity of the selected cluster, 2. size and shape of the cluster, and 3. existence of high Production-Index values inside a selected cluster with high Cluster-Index values. Based on these criteria, locations of the new wells were selected and two such locations are shown in **Figure 37B (Figure 18)**, one with high continuity and potential for high production and one with low continuity and potential for low production. The neighboring wells that are already in production confirm such a prediction as shown in **Figure 37B (Figure 18).**

9. Fractured Reservoir Characterization

In particular when we faced with fractured reservoir characterization, an efficient method of data entry, compiling, and preparation becomes important. Not only the initial model requires considerable amount of data preparation, but also subsequent stages of model updating will require a convenient way to input the new data to the existing data stream. Well logs suites provided by the operator will be supplied to the project team. We anticipate a spectrum of resistivity, image logs, cutting and core where available. A carefully designed data collection phase will provide the necessary input to develop a 3-D model of the reservoir. An optimum number of test wells and training wells needs to be identified. In addition, a new technique needs to be developed to optimize the location and the orientation of each new well to be drilled based on data gathered from previous wells. If possible, we want to prevent clustering of too many wells at some locations and undersampling in other locations thus maintaining a level of randomness in data acquisition. The data to be collected will be dependent on the type of fractured reservoir

The data collected will also provide the statistics to establish the trends, variograms, shape, and distribution of the fractures in order to develop a nonlinear and non-parametric statistical model and various possible realizations of this model. For Example, one can use Stochastic models techniques and Alternative Conditional Expectation (ACE) model developed by Breiman and Friedman [1985] for initial reservoir model prediction This provides crucial information on the variability of the estimated models. Significant changes from one realization to the other indicate a high level of uncertainty, thus the need for additional data to reduce the standard deviation. In addition, one can use our neuro-fuzzy approach to better quantify and perhaps reduce the uncertainties in the characterization of the reservoir.

Samples from well cuttings (commonly available) and cores (where available) from the focus area can also be analyzed semi-quantitatively by XRD analysis of clay mineralogy to determine vertical variability. Calibration to image logs needs to be performed to correlate fracture density to conventional log signature and mineralogical analysis.

Based on the data obtained and the statistical representation of the data, an initial 3-D model of the boundaries of the fractures and its distribution can be developed. The model is represented by a multi-valued parameter, which reflects different subsurface properties to be characterized. This parameter is derived through integration of all the input data using a number of conventional statistical approaches.

A novel "neuro-fuzzy" based algorithm that combines the training and learning capabilities of the conventional neural networks with the capabilities of fuzzy logic to incorporate subjective and imprecise information can be refined for this application. Nikravesh [1998a, b] showed the significant superiority of the neuro-fuzzy approach for data integration over the conventional methods for characterizing the boundaries. Similar method with minor modifications can be implemented and tested for fractured reservoirs.

Based on this information, an initial estimate for distribution of reservoir properties including fracture shape and distribution in 2-D and 3-D spaces can be predicted. Finally, the reservoir model is used as an input to this step to develop an optimum strategy for management of the reservoir. As data collection continues in the observation wells, using new data the model parameters will be updated. These models are then continually evaluated and visualized to assess the effectiveness of the production strategy. The wells chosen in the data collection phase will be designed and operated through a combination of an intelligent advisor.

10 Future Trends and Conclusions

We have discussed the main areas where soft computing can make a major impact in geophysical, geological and reservoir engineering applications in the oil industry. These areas include facilitation of automation in data editing and data mining. We also pointed out applications in non-linear signal (geophysical and log data) processing. And better parameterization of wave equations with random or fuzzy coefficients both in seismic and other geophysical wave propagation equations and those used in reservoir simulation. Of significant importance is their use in data integration and reservoir property estimation. Finally, quantification and reduction of uncertainty and confidence interval is possible by more comprehensive use of fuzzy logic and neural networks. The true benefit of soft computing, which is to use the intelligent techniques in combination (hybrid) rather than isolation, has not been demonstrated in a full extent. This section will address two particular areas for future research: hybrid systems and computing with words.

10.1 Hybrid Systems

So far we have seen the primary roles of neurocomputing, fuzzy logic and evolutionary computing. Their roles are in fact unique and complementary. Many hybrid systems can be built. For example, fuzzy logic can be used to combine results from several neural networks; GAs can be used to optimize the number of fuzzy rules; linguistic variables can be used to improve the performance of GAs; and extracting fuzzy rules from trained neural networks. Although some hybrid systems have been built, this topic has not yet reached maturity and certainly requires more field studies.

In order to make full use of soft computing for intelligent reservoir characterization, it is important to note that the design and implementation of the hybrid systems should aim to improve prediction and its reliability. At the same time, the improved systems should contain small number of sensitive user-definable model parameters and use less CPU time. The future development of hybrid systems should incorporate various disciplinary knowledge of reservoir geoscience and maximize the amount of useful information extracted between data types so that reliable extrapolation away from the wellbores could be obtained.

10.2 Computing with Words

One of the major difficulties in reservoir characterization is to devise a methodology to integrate qualitative geological description. One simple example is the core descriptions in standard core analysis. These descriptions provide useful and meaningful observations about the geological properties of core samples. They may serve to explain many geological phenomena in well logs, mud logs and petrophysical properties (porosity, permeability and fluid saturations). Yet, these details are not utilized due to the lack of a suitable computational tool. Gedeon et al.(1999) provided one of the first attempts to relate these linguistic descriptions (grain size, sorting, matrix, roundness, bioturbation and lamina) to core porosity levels (very poor, poor, fair and good) using intelligent techniques. The results were promising and drawn a step closer to Zadeh's idea on computing with words (Zadeh, 1996).

Computing with words (CW) aims to perform computing with objects which are propositions drawn from a natural language or having the form of mental perceptions. In essence, it is inspired by remarkable human capability to manipulate words and perceptions and perform a wide variety of physical and mental tasks without any measurement and any computations. It is fundamentally different from the traditional expert systems which are simply tools to "realize" an intelligent system, but are not able to process natural language which is imprecise, uncertain and partially true. CW has gained much popularity in many engineering disciplines (Zadeh, 1999a and 1999b). In fact, CW plays a pivotal role in fuzzy logic and vice-versa. Another aspect of CW is that it also involves a fusion of natural languages and computation with fuzzy variables.

In reservoir geology, natural language has been playing a very crucial role for a long time. We are faced with many intelligent statements and questions on a daily basis. For example: "if the porosity is high then permeability is likely to be high"; "most seals are beneficial for hydrocarbon trapping, a seal is present in reservoir A, what is the probability that the seal in reservoir A is beneficial?"; and "high resolution log data is good, the new sonic log is of high resolution, what can be said about the goodness of the new sonic log?"

CW has much to offer in reservoir characterization because most available reservoir data and information are too imprecise. There is a strong need to exploit the tolerance for such imprecision, which is the prime motivation for CW. Future research in this direction will surely provide a significant contribution in bridging reservoir geology and reservoir engineering.

Given the level of interest and the number of useful networks developed for the earth science applications and specially oil industry, it is expected soft computing techniques will play a key role in this field. Many commercial packages based on soft computing are emerging. The challenge is how to explain or "sell" the concepts and foundations of soft computing to the practicing explorationist and convince them of the value of the validity, relevance and reliability of results based on the intelligent systems using soft computing methods.

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