Soft computing for qualitative and quantitative seismic object and reservoir property prediction

Part 2: Fuzzy Logic Applications

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This is the second instalment of the series of review papers on soft computing applications in the petroleum industry. In this paper Fred Aminzadeh and David Wilkinson focus on fuzzy logic applications, including a brief overview of fuzzy logic technology, recent applications of fuzzy logic in various exploration and development scenarios, and a proposed framework to use fuzzy logic for seismic stratigraphy analysis and to explore applications of fuzzy differential equations.

In the companion paper to this series (Aminzadeh and de Groot, 2004), the main advantages of soft computing were highlighted. Among them were integrating information from various sources with varying degrees of uncertainty. Geosciences data used in exploration are inherently imprecise, uncertain and fuzzy.

This, combined with many linguistic rules and subjective treatment of the data, make it a good candidate for the use of fuzzy set theory for the processing, analysis and interpretation of E&P data. Figure 1, from Wilkinson et al (2003), illustrates the difficult task of modelling and analyzing the mother earth (geologic outcrops) with numerical (in this case seismic) measurements.

The main advantage of fuzzy logic is its versatility in combining the quantitative data and qualitative information and subjective observation and rules. Given the nature of the information available for interpretation (such as seismic data, well logs, geological and other geosciences data) fuzzy sets theory can help in developing an appropriate framework to carry out quantitative analysis of the information and data which are the aggregate of both qualitative and quantitative types.

> 'As complexity increases precise statements lose meaning and meaningful statements lose precision'
>
> *Lotfi Zadeh, inventor of fuzzy logic*

After a brief overview of prior work, we give several examples of applications of fuzzy logic in exploration.

What is Fuzzy Logic?

Fuzzy logic, which is a combination of fuzzy set theory and fuzzy rule based methods, was introduced by Lotfi Zadeh, a professor at the University of California at Berkeley, in the 1960s. It was specifically developed to handle data that are allowed to be both ambiguous and imprecise.

There are several fundamental differences between fuzzy logic and the traditional probability theory and Boolean algebra. The rigid boundaries of the latter such as (black and white), (yes or no), (true or false), (p (a) = 1-p (not a)), (0 or 1) are smoothed out in fuzzy logic. Having the choice between two groups, one does not need to belong to one or the other. Through 'membership functions', an item can be a

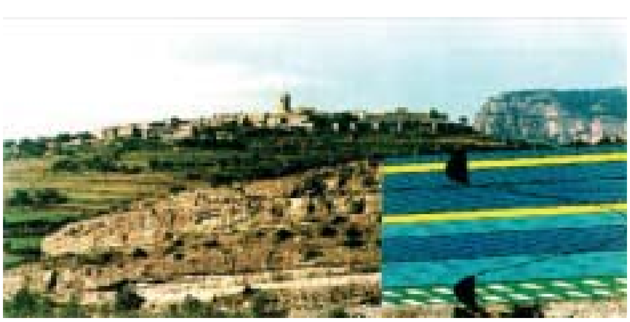

Figure 1 *Illustration of inherent fuzziness in geology and the corresponding seismic data*

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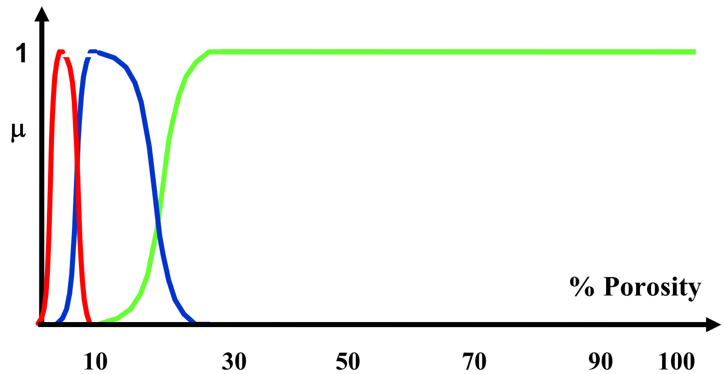

Figure 2 *Representation of low porosity (red), average porosity (blue) and high porosity (green) through membership function*

member of two or more groups with different degrees of membership grades simultaneously. Fuzzy logic is a non-traditional logic addressing Bertrand Russell's concern: 'All traditional logic habitually assumes that precise symbols are being employed. It is therefore not applicable to this terrestrial life, but only to an imagined celestial one. The law of excluded middle is true when precise symbols are employed, but it is not true when symbols are vague, as, in fact, all symbols are.'

In fuzzy logic, everything is a matter of degree. Since fuzziness or 'gray area' is present in nearly everything we do, fuzzy logic with its 'degree of membership' concept allows proper treatment of 'multi-valence'. Unlike classical logic which is based on crisp sets whose members are either 'True' or 'False', fuzzy logic views problems as having a degree of 'Truth.' Fuzzy logic is based on the concept of fuzzy sets whose members may be 'True' or 'False' or any number of gradations between 'True' and 'False.' Another way of expressing this is that a member of a fuzzy set may have varying amounts of both 'True' and 'False.' In classical or crisp sets, the transition between membership and non-membership in a given set for an element in the universe is abrupt (crisp). For an element in a universe that contains fuzzy sets, this transition can be gradual rather than abrupt. Therefore, 'fuzzy' and 'fuzziness' can be defined as having the fuzzy set characteristic. Mapping and sets in fuzzy theory are described and characterized as membership functions. Figure 2 shows how concepts such as 'low porosity', 'average porosity' and 'high porosity' could be represented. Naturally, such subjective definitions may be different for different petroleum systems.

It is clear that there is a fundamental difference between probability and the concept of membership grade. Probability statements are about the likelihood of an outcome: an event either occurs or it does not, and one can assign odds to it. But in the fuzzy world, one cannot state unequivocally whether an event has occurred or not, one can only postulate the extent to which the event occurred. In the process of dividing all the reservoirs into three categories using the fuzzy concept we observe two things: First, there is an overlap between classes. A reservoir with a porosity of 12% is simultaneously a member of the mid porosity and high porosity reservoir classes, albeit with different membership grades. Second, there is a smooth transition for membership grades (rather than going from 1 to 0 abruptly). This eliminates the need to establish rigid boundaries when translating linguistic terms to computer language.

In the past several years fuzzy logic has become an increasingly important problem-solving methodology in the realms of soft computing and applied computational intelligence. It provides an elegant way to make definitive conclusions based on noisy, imprecise, sparse or incomplete input information. This, coupled with its ability to allow seamless incorporation of additional data into highly complex systems and to do it with mostly 'white box' methods, makes fuzzy logic an attractive alternative to conventional techniques. Kosko (1993), in the book titled *Fuzzy Thinking* describes fuzzy logic, and its relevance to many real life (and death!) issues from politics to religion and from philosophy to washing machines. He argues that for thousands of years (since Aristotle) in Western philosophy, the world is either black or white, right or wrong, to be or not to be and all or nothing. In contrast, Eastern philosophy (starting with Buddha and then the Sufis) sees the world from a different perspective, with the unity of 'ying' and 'yang' and allowing coexistence of 'to be' and 'not to be'. Such openness to ambiguity is the essence of fuzzy logic.

Fuzzy logic in geoscience.

As in many other disciplines, earth scientists are confronted with the need to deal with many diverse data types which come from a wide variety of sources, have different scales and different degrees of imprecision and uncertainty. It is not uncommon to hear our data described as noisy, imprecise, sparse, incomplete, etc. To further complicate matters, it is often the case that we must resort to grossly oversimplified models of the large and complex systems that we attempt to analyze.

In spite of this, many of our data processing and analysis techniques are able to function adequately only when both the model and data are known with certainty. In this situation it is not surprising that the results of our analysis have a high degree of sensitivity to inadequacies in both the model and data components.

To combat this problem, it is usual to attempt to process the data to the point where application of our precise algorithms can give a reasonable answer. A second alternative would be to preferentially employ methodologies that are tolerant to the imprecision in the input data.

In order to utilize a fuzzy logic rule-based approach it is necessary to gather together all the data and non-numeric information relevant to the project. For typical geoscience applications, possible knowledge base components might include:

- Data Elements
  - o Seismic (3D, 4D, 4C, prestack),
  - o Well logs, MWD
  - o Cores, thin sections
  - o Production data
- Knowledge elements
  - o Theoretical relationships
  - o Heuristic rules of thumb, empirical rules
  - o Expert knowledge
  - o Attribute to property mappings
  - o Geological analogues
  - o Statistical models, simulator 'tricks'
- Definitions of the fuzzy partitions of the input space (i.e. which properties are of interest, Vp, Vs, f, Kv, Kh, lithology, Sw…)
- Membership functions (i.e. what shape do the membership functions have?)

Over the last 25 years, there have been several attempts to incorporate fuzzy logic into the geosciences. Chappaz (1977) and Bois (1983, 1984) proposed the use of fuzzy set theory in the interpretation of seismic sections. Bois used fuzzy logic as a 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 suggested that these types of error and fuzziness cannot be taken into consideration by traditional mathematics: however, they are accounted for by fuzzy set theory. He also concluded that, using fuzzy set theory, it is possible to extract geological information from seismic data. Therefore, one could, in principle, predict the boundary of a reservoir in which hydrocarbon exists.

Griffith (1987) used fuzzy logic to predict different stratigraphic units from drilling data. He used subjective classifications of pagioclase feldspars involving many overlapping membership functions with different percentages of anorthite. He then used drilling data with different variables such as rotary speed, bit weight, mud weight and torque among others to create numerical lithostratigraphic units from such data. The results obtained were consistent with those measured directly from well logs. Lashgari (1990) also reported a series of applications of fuzzy sets theory in geostatistical analysis and clustering of seismic attributes using fuzzy K-means method. An and Moon, (1990) used fuzzy set theory to integrate geological and geophysical data. Aminzadeh (1994) highlighted applications of fuzzy expert systems in oil exploration. Tomhane et al (2002) adopted qualitative information based on linguistic descriptions (e.g. 'low,' 'medium' and 'high') which are commonly used by expert geologists for permeability prediction from well logs and compared them against traditional methods based on semi-empirical equations.

Most recently, there have been three books on applications of soft computing in exploration. The three books, Wong et al (2002), Nikravesh et al (2003) and Sandham et al (2003), all have sections highlighting some of applications of fuzzy logics in the oil industry.

Examples of recent applications

In this section we highlight a few recent applications of fuzzy logic and point to potentially high impact uses in different earth science problems.

Fuzzy differential equations

Partial differential equations (PDE) are at the foundation of physical laws governing two different oil industry applications: Darcy's law and wave equation. The first has to do with the movement of fluids through porous media. The second governs propagation of waves (both elastic and electromagnetic) through the subsurface. How to solve these equations, under various assumptions for their respective parameters, has been the subject of numerous doctoral dissertation topics, academic research programmes, oil and gas company technology development activities and service companies' software packages. They all attempt to make the solution more feasible, assumptions more realistic and approximations more acceptable.

Many geophysical techniques such as migration, DMO, wave equation modelling 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 can lead to unrealistic situations (for example, medium velocities for seismic wave propagation or fluid flow for Darcy equation). Stochastic parameters or alternatively, fuzzy coefficients can provide us with a more practical characterization. Fuzzy coefficients for PDEs can prove to be more realistic and easy to parameterize.

As was suggested in Aminzadeh (1995), using wave equations with random or fuzzy coefficients to describe subsurface velocities and densities in statistical and membership grade terms, enables a better description of wave propagation in the subsurface, particularly when a substantial amount of heterogeneity is present. Moreover, 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.

Given the complex nature of hydrocarbon bearing reservoirs and the considerable heterogeneity of the rock formations through which seismic waves propagate or fluids (oil, gas and water) flow, parameterization of those equations is a formidable task. The extremely sparse nature of the available data, coupled with very limited direct measurements (well logs, flow rates, and core samples) makes the modelling and validation job even more difficult. In addition, different types of uncertainties, measurement errors, and approximations associated with idealistic assumptions of the medium with respect to governing physical laws, makes the theoretical equations less reliable.

Once we recognize the inherent inadequacies of the conventional mathematical techniques and classical equations based on deterministic and crisp parameterization, we understand the need for alternatives. Even if we have to substantially rewrite the book on reservoir simulation and geophysical imaging, we do need to move to stochastic and fuzzy-logic based methods. That is, we need to use wave equations comprised of random or fuzzy coefficients describing subsurface geometry, velocities and densities. This will enable us to describe and parameterize the medium through which acoustic waves propagate, particularly when a substantial amount of heterogeneity is present, more effectively.

Likewise, Darcy's law, describing the permeability of rocks in terms of 'measurable' quantities, can be generalized to account for imprecision, uncertainty and measurement errors. Permeability is an important reservoir property. It controls the flow rate and directional movement of different fluids (namely gas, water and oil) through the reservoir formations. Darcy's method, based on a partial differential equation, is established for an idealized situation dealing with 'horizontal linear flow of an incompressible fluid'. Realistically, in a highly heterogeneous and anisotropic, multi-phase fluid environment, these assumptions are too restrictive and a more sophisticated and rigorous treatment of the problem becomes necessary.

A recent book by Nikravesh et al (2004) is a first step towards introducing fuzzy partial differential and fuzzy relation equations to the oil industry. It is envisioned that these methods will begin to find some relevance and application in many petroleum industry problems. This will enable us to treat model parameterization, inversion and reservoir simulation more effectively and with more consistency with the real problems we are facing every day. Using fuzzy differential equations, we no longer need to find the illusive 'precise' equations to describe the 'precise physical phenomena', for solving our increasingly complex problems.

Stratigraphic interpretation

One of the major strengths of fuzzy logic lies in the concept of a linguistic variable. This is a concept that has particular importance for earth science. While much of geophysical and geological data is numerical in nature, there have been many ad hoc attempts to include semantic information in the knowledge discovery process. Fuzzy logic provides a robust framework within which this type of data integration occurs in a natural way. Here we show how many stratigraphic concepts could be formulated through fuzzy logic, relying on its ability to handle linguistic qualifiers. This example is taken from Aminzadeh and Simaan (1991). Three types of deltaic facies, prodelta, delta-front, and alluvial are characterized according to their seismic response by the following guidelines adopted from the classic paper by Brown and Fisher (1977). The words in italics highlight the inexact and fuzzy nature of these rules:

<u>Prodelta and distal delta-front, barrier facies:</u> Reflection patterns for these facies in dip sections are *horizontal to steeply inclined,* oblique, layered patterns within a zone that *ranges from poorly layered to reflection-free or locally chaotic*. Oblique reflections *may* converge (and baselap) downward (basinward). In strike sections, the facies *commonly* exhibit convex-upward, *conformable drape-to-mounded-chaotic,* or reflection-free patterns with *some evidence* of channel or gully erosion. On the relict shelf, the prodelta reflections are *discontinuous except for a few strong reflections,* amplitudes are *generally low* except for reflections with *moderate continuity,* and spacing is very *erratic*.

<u>Delta-front, barrier-bar facies:</u> Reflection patterns in dip sections are *horizontal to slightly inclined,* parallel-layered *near* the base, grading upward *irregularly* into *chaotic or reflection-free* patterns with *common convex-upward diffractions* and *poorly defined,* mounded reflections. *Subtle, inclined reflections* within chaotic zones *may* represent delta-front or barrier-bar of flap and, hence, *may* constitute internal time lines. In a strike section, the basal reflections of the zone *exhibit drape patterns* and *local chaotic,* to *reflection-free,* zones *display subtle, parallel-layered to draped,* reflections and *abundant* diffractions. Basal reflections exhibit strong continuity, but c*ontinuity diminishes upward* in the unit. *The best continuity* occurs in dip sections. Amplitudes are *moderate to high* in basal, high-continuity reflections, but low in chaotic intervals; spacing is *moderately uniform* in basal reflectors, but erratic in the upper part of the zone.

<u>Alluvial, delta-plain facies:</u> Reflection patterns in dip sections are *principally horizontal,* parallel, *rarely divergent layered to locally reflection-free;* locally, erosional channels *may be* inferred. In strike sections, the reflections are *weak, parallel-layered to subtle-mounded, chaotic-to-drape* patterns.

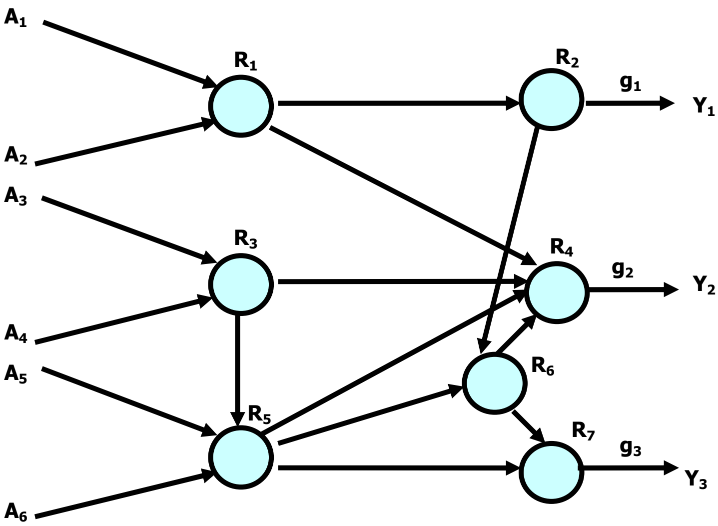

Figure 3 *A schematic diagram for Fuzzy Rules of Table 1 to distinguish different facies based on their seismic response*

Continuity of reflections range from *excellent to fair* in dip sections, but continuity is *poor to fair in strike sections;* amplitude is variable (high in continuous reflections and poor in chaotic zones); and spacing is *very regular* in zones of *high-continuity reflections* but *irregular* in the remainder of the unit.

Given the nature and structure of rules such as these, to implement them in an expert system based on classical (exact) mathematics is nearly impossible. The obvious solution is the use of a system based on fuzzy inference. The following data (facts) are assumed available.

$A_{1.}$ dip section reflection pattern,
$A_{2.}$ strike section reflection pattern,
$A_{3.}$ dip section reflection continuity,
$A_{4.}$ strike section reflection continuity,
$A_{5.}$ dip section reflection strength, and
$A_{6.}$ strike section reflection strength.

Note that A_1 and A_2 are fuzzy quantities defined over the fuzzy subset X_1 with membership grades of f_1^i and f_2^i, i = 1, 2, . . . I, where I is the number of elements in X_1. Table 1 outlines the described rules. Also, subsets of X_1, X_2, X_3, with all the possible elements in them, are defined. For example:

X_1. (Horizontal, oblique, vertical, layered, convex upward, convex downward, drape mounded).
X_2; (Locally chaotic, discontinuous reflections, continuous reflections)
X_3; (Low reflection amplitude, high reflection amplitude, reflection free).

Given the fuzzy information and rules, the input data goes through a fuzzy inference mechanism, the result of which is a fuzzy classification of the data into possible stratigraphic types; prodelta, delta front, alluvial (*Y, Y_2, and Y_3*) with different membership grades (g_1, g_2, g_3, . . .). Figure 3 shows a possible fuzzy inference network for this example.

Figure 3 is only for illustration and is not meant to incorporate the rules of Table 1. However, the figure does show, conceptually, how a series of fuzzy rules can be combined to reach a fuzzy outcome. This example illustrates the basic

	Prodelta & distal data front Barrier facies	Delta front, barrier facies	Alluvial-delta-plain facies
A_1 **Dip section reflect pattern**	Horizontal to steeply inclined, Oblique (layered to poorly layered pattern)	Horizontal to slightly inclined, parallel layered near the base, common convex upward reflection	Principally horizontal, parallel
A_2 **Strike section reflection pattern**	Convex upward	Drape pattern for the basal reflections	Parallel layered to subtle-mounded, chaotic to drape
A_3 **Dip section reflection continuity**	Locally chaotic	Better continuity than the strike section	Excellent to fair
A_4 **Strike section reflection continuity**	Mostly discontinuous reflection	Basal reflections exhibit strong continuity diminishing upward in the unit	Poor to fair
A_5 **Dip section ref. Strength**	Weak reflection to reflection free, low amplitude in relict shelf except for those with moderate continuity	High to moderate amplitude in basal, high continuity reflection but low in chaotic areas	Weak

Table 1 *A set of rules to distinguish different facies based on their seismic response*

concept of knowledge representation using fuzzy logic without going into any detailed theoretical discussion.

Modelling reservoir permeability using seismic and log data

Permeability is a measure of fluid conductance in porous media. It is the most difficult reservoir property to estimate but of great importance to reservoir management decisions, such as drilling location and water injection. Two types of data were provided for this work: well log data and core data. In this method, the permeability transform process is first established using the control data and then applied everywhere in the reservoir.

It is commonly observed that permeability is related to other rock properties, although a theoretical mathematical equation to describe such a relationship does not exist. The objective of this work is to build a process that approximates such a relationship. The particular rock properties used in this methodology are the elastic parameters (velocity, density and porosity) derived from either log or seismic data. This was essential so that the model could be used to estimate

	Sand	Shaly Sand	Sandy Shale	Shale	High Imp. Sand
High Perm	148	81	83	20	43
Medium Perm	29	23	76	-	-
Low Perm	11	27	139	147	-
Total	188	131	298	167	43

Table 2 *Input data set*

reservoir permeability everywhere seismic data is available. We carry out this modelling task using Genetic Programming (GP), Koza (1992) and Adaptive-Network-based Fuzzy Inference Systems (ANFIS), and Jang (1997).

A hybrid GP-fuzzy system

Frequently, permeability is highly dependent on the nature of the rock formations (litho-facies). Each litho-facies can have a wide range of permeability values and even more troubling, can exhibit rapid permeability variations. Moreover, different permeability ranges demonstrate different geological characteristics. As a result, it is virtually impossible to build one generic transform that gives good permeability estimation for all types of reservoir rocks. We therefore adopt a divide-and-conquer approach to build the permeability transform system:

- The first layer of the system identifies the lithology group.
- The second layer of the system predicts permeability range (low, med, high).
- The last layer of the system estimates the actual permeability value.

To test the system, the log data from five wells were used. All of them have matching core permeability data. Table 2 gives the number of data in each lithology group and permeability range. These groups and ranges are established based on geological knowledge and the analysis of the data sets. The total number of data points is 827.

One of the classical ways to estimate permeability is use of the V-shale estimate. At the well locations this can be obtained from the gamma ray log. Upon cross-plotting V-shale vs. permeability (Figure 4), it is apparent that these two have a complicated relationship, although in general the higher the V-shale value, the lower the permeability. The standard approach is to generate an S-curve to fit these data and use this to predict permeability within the reservoir. We will see that this usually results in a poor estimate of actual permeability. Part of our seismic data analysis is the identification of lithology. Hence, we can use this ability to perform this analysis on a per lithology basis. An analysis of the X-plot data suggests four lithology groups: sand, shaly sand, sandy shale and shale with the V-shale cut points at 0.15, 0.4 and 0.75.

We can see from these data that there does indeed exist both a wide range and a rapid variation of permeability values within each lithologic facies. It is clear that a simple regression on Vshale will not be sufficient to give realistic permeability estimates. Consequently, the usual practice is to perform a regression on Vshale, plus some other log properties. In this case the S-curve is a function of Vshale and porosity.

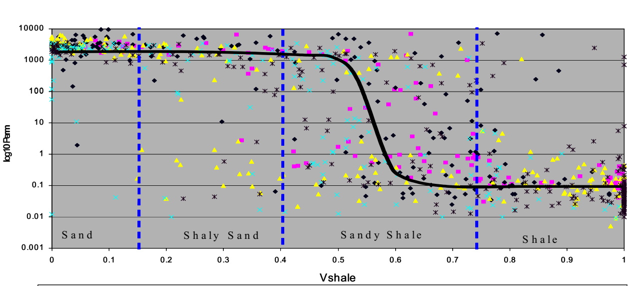

Figure 4 *V-shale vs. log10 permeability.*

The fuzzy inference system

The genetic algorithms (GA) used to train the classifiers for predicting permeability ranges will be discussed in a subsequent paper on the topic. Here, we discuss the ANFIS modelling tool that is a TSK fuzzy inference system based on the given input and output data. A TSK fuzzy system has the following structure: The first component is a set of input membership functions (MFs). An MF maps crisp inputs to linguistic values or labels. An MF can have any shape, such as triangular, Gaussian and trapezoidal, as long as it varies between 0 and 1.

The transformation of a crisp input into degree (between 0 and 1) of match with a linguistic value is called 'fuzzification'. Fuzzy rules are conditional statements in if-then format. The 'if' part consists of linguistic values and fuzzy operators (AND, OR, NOT). The 'then' part is a first order linear equation (*ax+by+c*). An example TSK fuzzy rule is given here:

- *If porosity is high and density is low, permeability = -42572*porosity-53/velocity-115807*density + 260911.*

Fuzzy inference is a method that interprets the input values and, based on the fuzzy rules, assigns output values. In a TSK system, the output value is calculated based on the firing strength *wi* of each rule. ANFIS represents a TSK system as a feed-forward network architecture that is similar to a neural network

The first learning step determines the number of fuzzy rules (layer 2). The clustering algorithm first partitions the data into groups and then generates a minimum number of rules to distinguish the fuzzy qualities associated with each of the groups. The shapes of input membership functions (layer 1) are not learned but specified by users. Depending on the shapes of input membership function selected, different parameters (e.g. mean and standard deviation for Gaussian) are initialized. Meanwhile, the output parameters (e.g. the coefficients in the linear equations) are initialized. The second learning step adjusts input and output parameters to minimize the error. More specifically, in the forward pass, training inputs go forward till layer 4 and the output parameters are identified by the least squared estimate. In the backward pass, the error rates propagate back and the input MF parameters are updated by gradient decent.

Performance comparison with the conventional approach shows that the hybrid system (Perm-FIS) gives permeability estimations that are closer to the core permeability (Perm-Core). Figure 5 shows the conventionally estimated core permeability vs the actual core permeability for the five wells used in the study.

While the general agreement is reasonable, there is a broad degree of scatter in these plots, reflecting the inability of a single transform to adequately account for the complexity of the actual permeability distribution. The hybrid sys-

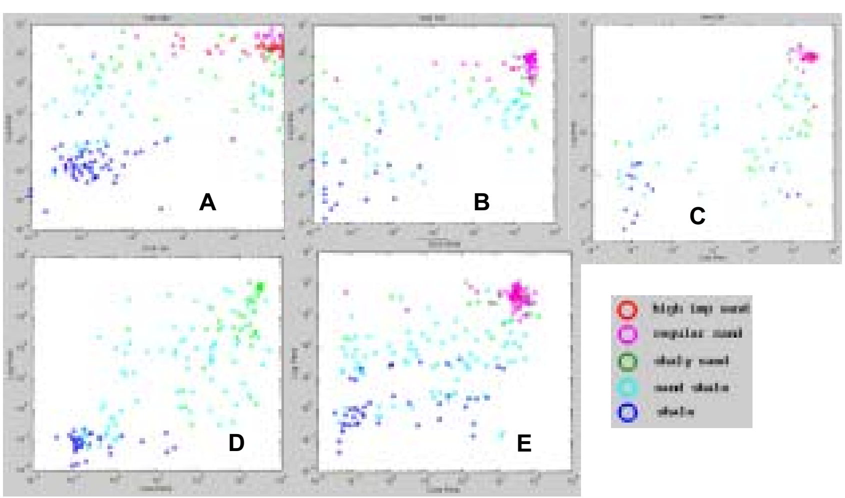

Figure 5 *The original regression transform performance (estimations vs. core permeability).*

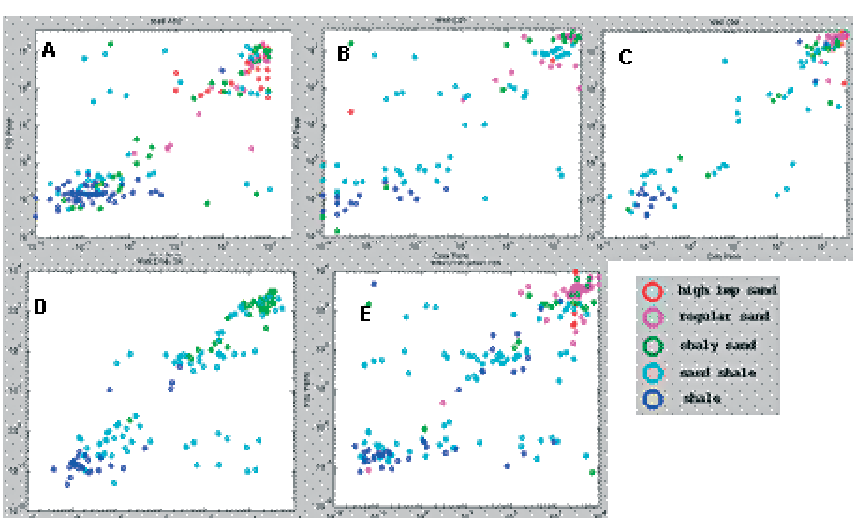

Figure 6 *The hybrid system performance (estimations vs. core permeability).*

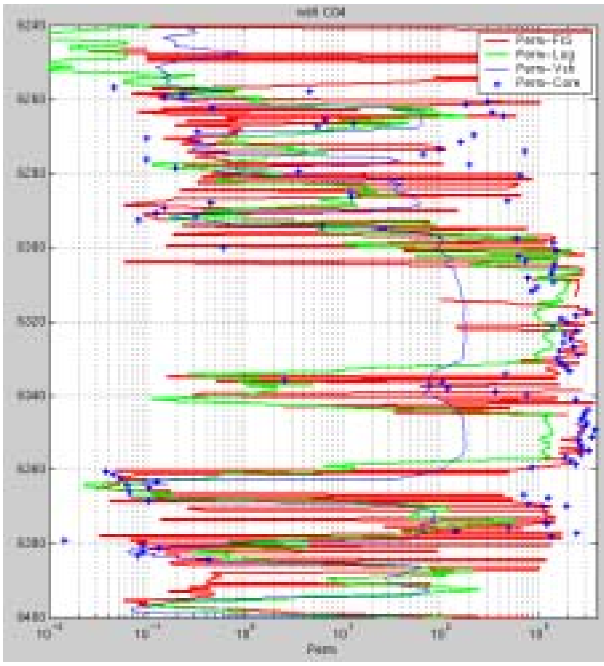

Figure 7 *Performance of different methods overlain on the same permeability log plot together with the actual core sample values.*

tem (Perm-FIS) results give permeability estimations that are much closer to the actual core permeability (Perm-Core), Figure 6.

Figure 7 shows performance of each of the (a) regression on Vshale alone, (b) regression on Vshale and porosity and (c) the fuzzy-hybrid system methods. It is clear to see that the Vshale alone result is not acceptable, and it is further evident that the fuzzy-hybrid system outperforms the usual best practice method.

Prediction of permeability from porosity, velocity and attenuation

Here a neural-fuzzy model is developed for nonlinear mapping and rule extraction (knowledge extraction) between porosity, grain size, clay content, P-wave velocity, P-wave attenuation and permeability. This section is adapted from Nikravesh and Aminzadeh (2001). The well data set includes information on grain size, porosity, clay content, P- wave velocity, P-wave attenuation and measured permeability (from right to left in Figure 8). These data were originally used by Boadau (1997). The following rules are the basis for prediction of permeability from other measurements using fuzzy membership functions.

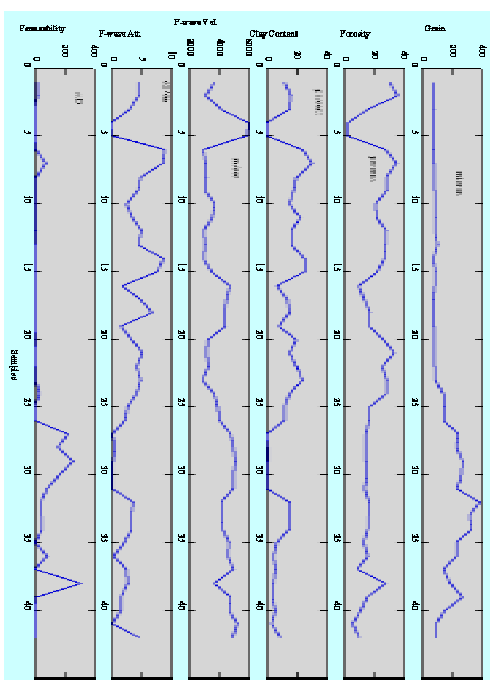

Figure 8 *Raw data (from Boadu, 1997)*

Porosity	*Clay Content*	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]

Table 3 *Boundary of rules extracted from data.*

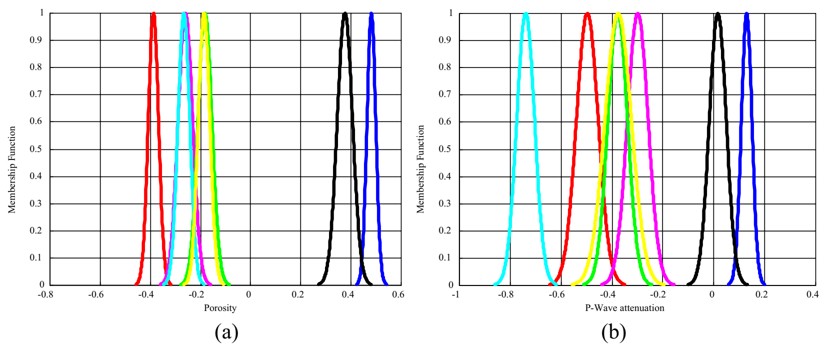

Figure 9 *Membership functions for different ranges of (a) porosity, (b) P-Wave attenuation*

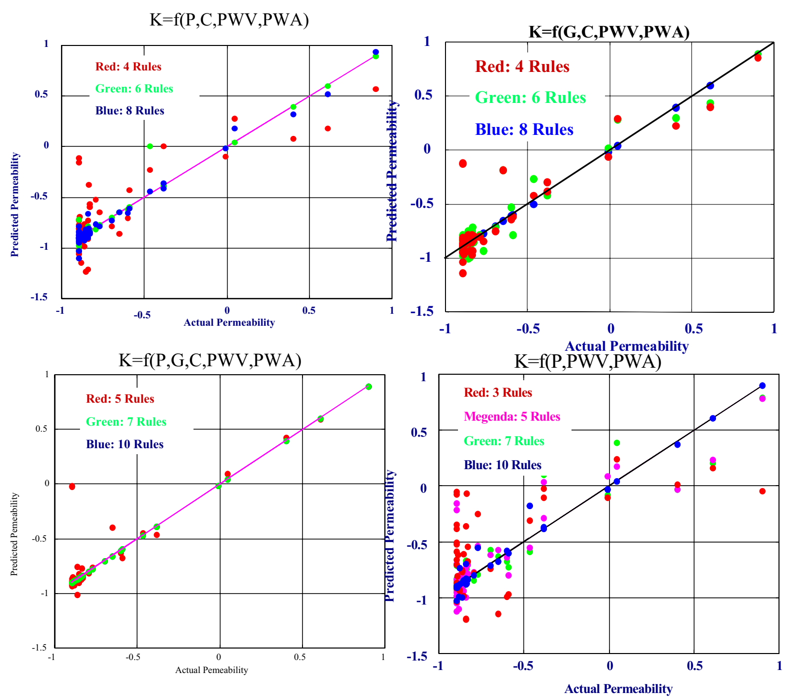

Figure 10 *Prediction results against the original measurements of permeability with different input data*

IF Rock Type= Sandstones
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 K*= 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 PWA P-wave attenuation and K, predicted permeability. Table 1 show typical rules extracted from the data. Note that for computational convenience all data from different logs are scaled uniformly between -1 and 1, and all the results are in this normalized Figure 8 Raw data (from Boadu, 1997) 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 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.

In Table 3, Column 1 through 5 show the membership functions for porosity, grain size, clay content, P-wave velocity, and P-wave attenuation respectively were derived for each of the above properties. For example, Figures 8a and 8b show such functions for porosity content and P-wave attenuation. Different colour curves represent extremely low, very low, low, average, high, very high and extremely high porosity and attenuations (from left to right).

Based on these functions and the rules described above, permeability was predicted. Figure 10 shows the resulting permeability predictions based on a different set of input data (1997) in that the most influential rock parameter on the attenuation is the clay content. In addition, this method has the capability to rank different components of the input data on their influence in prediction.

Conclusions

We have demonstrated the use of fuzzy logic in different aspects of exploration and development in the petroleum industry. In spite of the many applications, such as well log analysis, reservoir property prediction and stratigraphic analysis that have been presented, the full impact of fuzzy logic in geosciences is yet to be realized. As more applications come along, particularly the hybrid systems, it will become increasingly clear that fuzzy logic has a central role to play in the earth sciences. Perhaps the proposed implementation of fuzzy differential equations, both for formulating acoustic wave propagation in the earth or fluid flow in the reservoirs, will begin to more fully realize the potential of fuzzy logic.

References

Aminzadeh, F. and Simaan, M., Eds. [1991] *Expert Systems in Exploration,* SEG Publications, Tulsa,

Aminzadeh, F. [1996] Future Geophysical Technology Trends. *The Leading Edge,* **15**, 6, 739-742

Aminzadeh, F. [1994] Applications of Fuzzy Expert Systems in Integrated Oil Exploration, in *Soft Computing,* Eds., Aminzadeh. F. and Jamshidi, M., Prentice Hall.

An, P. and Moon, W. M. [1996] Application of fuzzy set theory for integrating geological and geophysical data. 60th Annual International. Meeting, SEG, *Expanded Abstracts,* 366-369.

Boadu, F.K. [1997]Rock properties and seismic attenuation: Neural network analysis, *Pure Applied Geophysics,* **149**, 507-524.

Bois, P. [1984] Fuzzy Seismic Interpretation, *IEEE Transactions on Geoscience and Remote Sensing,* Vol. GE-22, 6, 692-697.

Brown, L. F. Jr. and Fisher, W. L. [1977] Seismic-stratigraphic interpretation of depositional systems, examples from Brazilian Rift and Pull-Apart Basins, in E. E. Payton., Ed., *Seismic stratigraphic applications to hydrocarbon exploration,* AAPG Memoir 26, 281-248.

Griffiths, C. M. [1987] The nature of geologic representation language and consequent constraints on machine interpretation, in *Pattern Recognition and Image Processing,* Aminzadeh, F., Ed., Elsevier Science Ltd.

Jang, J-S. R. and Sun, C-T. [1997] *Neuro-Fuzzy and Soft Computing: A Computational Approach to Learning and Machine Intelligence,* Prentice Hall.

Kosko, B. [1993] *Fuzzy Thinking,* Hyperion, New York.

Koza, J. [1992] *Genetic Programming: On the Programming of Computers by Means of Natural Selection.* MIT Press, Cambridge, MA.

Lashgari, B. [1991] Fuzzy Classification with Applications, in Expert Systems in Exploration, Aminzadeh, F. and M. Simaan, Eds., *SEG publications,* Tulsa, 3-32.

Nikravesh, M. and Aminzadeh, F. [2001] Mining and Fusion of Petroleum Data with Fuzzy Logic and Neural Network Agents, *Journal of Petroleum Science and Engineering*, **29**, 221-238.

Nikravesh, M, Zadeh, L. A.; Korotkikh, V. [2004] Fuzzy Partial Differential Equations and Relational Equations Reservoir Characterization and Modeling Series. *Studies in Fuzziness and Soft Computing*, **142**, 347, Springer Verlag.

Nikravesh, M., Aminzadeh, F., Zadeh, L. A. [2003] *Soft Computing and Intelligent Data Analysis*, Elsevier.

Popolie, R. F. and Mendel, J. M. [1989] Heuristically constrained estimation for intelligent signal processing, in Simaan, M. and Aminzadeh, F., Eds, *Advances in geophysical data processing, Vol. 3, Artificial intelligence and expert system in petroleum exploration,* JAI Press, 107-133.

Sandham, W., Leggett, L. [2003] *Applications of Artificial Neural Networks and Fuzzy Logic,* Kluwer Academic Publisher.

Tamhane, D., Wong, P.M., Aminzadeh F. [2002] Integrating Linguistic Descriptions and Digital Signals in Petroleum Reservoirs, *International Journal of Fuzzy Systems*, **4**, 1, 586-591.

Wilkinson, D., Yu, T., Xie, D. [2003] *Genetic Programming Theory and Practice*. Kluwer Academic Publishers, 271–289.

Wong, P. M., Aminzadeh, F. and Nikravesh, M. [2002] Soft computing for Reservoir Characterization and Modeling, *Series Studies in Fuzziness and Soft Computing,* **80**, Physical Verlag, Springer.