A STATE-OF-THE-ART REVIEW OF FUZZY LOGIC FOR RESERVOIR EVALUATION

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ABSTRACT

The application of new mathematics using fuzzy logic has been successful in several areas of petroleum engineering. This paper reviews the state-of-the-art of fuzzy logic applied to reservoir evaluation, especially in the area of petrophysical properties prediction and lithofacies prediction from well logs. In this paper, we will also review some fuzzy methods that have been successfully applied to case studies. Besides using fuzzy logic in establishing the model itself, fuzzy logic is also used in some cases as pre-processing or post-processing tools. This paper will act as a guide for petroleum engineers to take advantage of these advanced technologies as well as those undertaking research in this field.

KEYWORDS

Fuzzy theory, fuzzy systems, well logs, fuzzy rule extraction, pre-processing.

INTRODUCTION

Two key issues in reservoir evaluation using well logs are the characterisation of formations and the prediction of petrophysical properties. A large number of techniques have been introduced to establish adequate interpretation models. The task is not simple, however, because of the complexity of different factors, which influence the log responses, and the increasing amount of downhole measurements employed. A large number of techniques have been introduced to establish an adequate interpretation model over the past 50 years (Balan et al, 1995). The way that reservoir evaluation is carried out has also changed considerably during the years due to the development in logging tools and methodologies. The analysis process has also undergone substantial changes due to the development and understanding of the physics of porous media and the rapid development of computer technology.

In the past few years, a technique that has emerged as an option for permeability determination is the Artificial Neural Network (ANN). Research has shown that an ANN can provide an alternative approach to permeability determination (Osborne, 1992; Wong et al, 1995). Most of the ANN based permeability determination models have used the Multi-layer Neural Network (MLNN) utilising the backpropagation learning algorithm. Such networks are commonly known as Backpropagation Neural Networks (BPNNs). A BPNN is suited to this application, as it resembles the characteristics of regression analysis in statistical approaches. ANNs perform analysis in a fundamentally different way from the traditional empirical and statistical approaches. ANNs can be used to address most of the factors that could possibly affect the accuracy of the model. An ANN does not require a prior assumption of the functional form of the dependency. It also offers a numerical model free of estimators and dynamic systems. In addition, an ANN possesses the capability to model complex non-linear processes with acceptable accuracy and has the ability to reject noise.

The main disadvantage of using ANNs is due to the inability to interpret the determination model. After an ANN is trained, it acts like a black-box. A user will have difficulty in understanding the large number of weights involved. In addition, the effects on the output are unpredictable if some weights are modified. This has opened out the new research area of using fuzzy systems as an alternative intelligent technique in establishing the determination model for reservoir evaluation. This paper acts as a review of the use of fuzzy systems in this field.

FUZZY THEORY

Fuzzy theory works on the basis derived from fuzzy logic (Zadeh, 1973; Klir and Yuan, 1995). A fuzzy logic allows for the degree of membership of an item in a set to be any real number between 0 and 1. This allows human observations, expressions and expertise to be modelled more closely. Fuzzy logic, which is different to Boolean logic, deals with degrees of membership or degrees of truth. It uses the continuum of logical values between 0 (completely false) and 1 (completely true). For example, the colour black and white employs the whole spectrum of colours, not just black and white. We accept that things can be partly black and partly white at the same time as shown in Figure 1.

Fuzzy set theory (Zadeh, 1973) works differently to traditional crisp set theory, in that for a class of objects

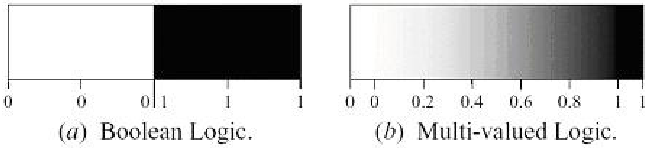

Figure 1. Boolean Logic vs Fuzzy (multi-valued) Logic (Negnevitsky, 2002)

there is no sharp boundary between those objects that belong to the class and those that do not. Figure 2 shows the comparison of crisp sets and fuzzy sets used to model whether a man is tall or not. In crisp sets, a man is considered tall when his height is 180 cm. A man whose height is 179 cm, however, will not be considered tall. As for fuzzy sets, the man whose height is 179 cm will still be considered tall with a degree of membership of around 0.8. Thus fuzzy sets produce more realistic modelling for real world problems.

The membership function of a fuzzy set A is denoted by:

$$A : X \rightarrow [0,1]$$

Once the fuzzy sets have been defined, it is possible to use them in constructing rules for fuzzy expert systems and in performing fuzzy inference. The three main components in a fuzzy system are fuzzification, fuzzy inference and defuzzification as shown in Figure 3. In fuzzification, all the values are converted to fuzzy inputs by using fuzzy membership functions. The common types of fuzzy membership functions are triangular, trapezoidal, gaussian and generalised bell. Triangular and trapezoidal types are most commonly used in engineering applications, as they are not as computationally complex as the other two. In fuzzy inference, the fuzzy rules that best match the input linguistic label are found. Then the corresponding output linguistic labels are taken as the output of the fuzzy inference. A single fuzzy if-then rule assumes the form *if x is A then y is B*, where *A* and *B* are linguistic labels defined by fuzzy sets on the ranges *X* and Y, respectively. In order to convert back to a crisp output value, defuzzification methods can be used. Fuzzy systems can produce more accurate results based on the basic idea of defuzzification. A defuzzification technique is used to calculate the conclusion by evaluating the degree of matches from the observation that triggered one or several rules in the model. This will lead to a better result by handling the fuzziness in the decision making (Negnevitsky, 2002).

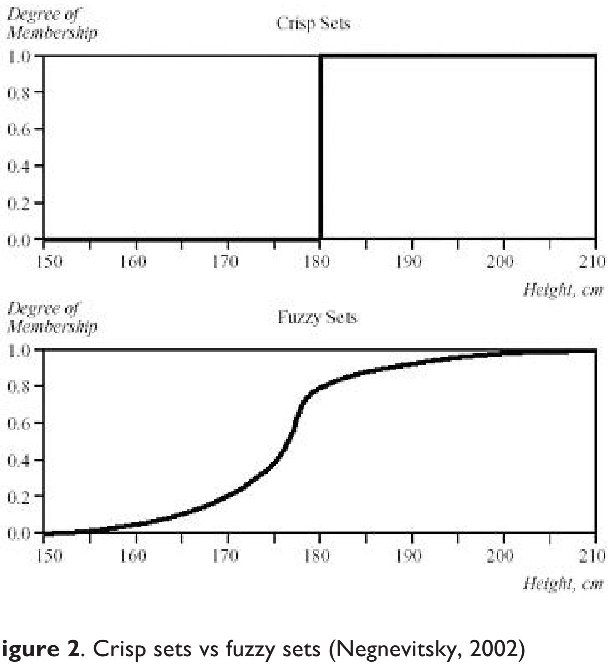

Figure 2. Crisp sets vs fuzzy sets (Negnevitsky, 2002)

Fuzzy sets allow some human expertise and decisions to be modelled more closely. Normally, a set of example data or knowledge from the analyst is used as the basic knowledge available to build the fuzzy rule base. Using knowledge from the analyst, fuzzy rules can be hand-coded into the determination model. With the availability of vast amounts of data, however, it is useful to extract knowledge from the available data directly. This has the advantage of the discovery of new knowledge or relations underlying the data. There are a few ways that the fuzzy rule base can be constructed from the available input-output data.

In classical fuzzy approaches from Zadeh (1973), and Mamdani and Assilian (1975), the basic idea is to calculate the conclusion by evaluating the degree of matches from the observation that triggered one or several rules in the model. In most fuzzy modelling or fuzzy control systems, experiments and simulations are set up to generate a set of data that best describes all the possible outcomes. After this, a human expert will create the set of fuzzy rules that best perform control or modelling. Normally, fuzzy rules generated in this manner will cover the whole universe of discourse by taking all the possibilities into account. A serious problem may occur, however, due to the high computational time and space complexity of rule bases used to describe the model with multiple input variables with proper accuracy. The exponential explosion allows little general systems application or real time application of the classical fuzzy algorithms where the number of input variables becomes large (Kóczy, 1993). For *k* input variables, and with *T* fuzzy linguistic terms, the number of fuzzy rules covering *X* is:

$$|R| = O(T^k)$$

which could be very high, unless *k* is very small. This exponential explosion in the number of rules is a major problem, hindering the application of fuzzy techniques beyond the area of fuzzy control systems. Besides, the time required in searching the large rule base to perform inference might become impractical for any potential applications. There is a challenge in fuzzy research to find ways to solve this problem.

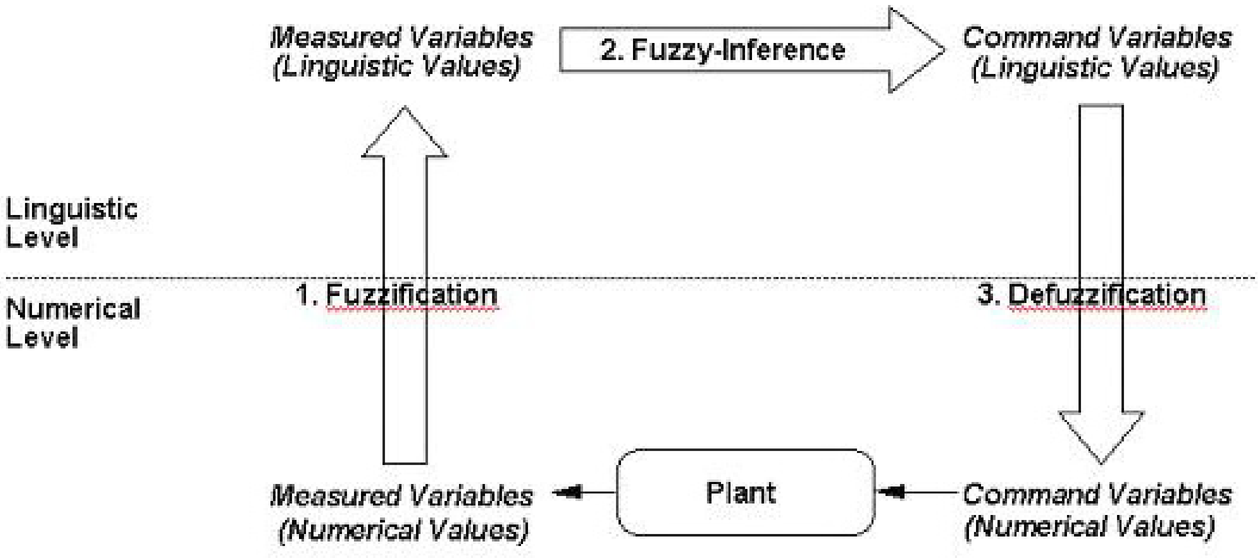

Figure 3. Main components in a fuzzy system

FUZZY APPLICATION REVIEWS

The new mathematics using fuzzy theory in establishing a determination model for reservoir evaluation has become a new technique in the last few years (Cuddy, 1997; Fung et al, 1997; Cuddy, 2000; Gedeon et al, 2002). As a fuzzy determination model relies on a set of fuzzy rules, it will be very difficult for a human analyst to hand code all the fuzzy rules required in the determination process. Fuzzy rule extraction techniques are normally used to extract fuzzy rules directly from the data. This can be observed in most of the papers reviewed in this section. The set of extracted fuzzy rules not only has to enhance the prediction results by better handling of uncertainties and fuzziness, but it should also be capable of expressing the underlying characteristics of the determination model in human understandable rules.

Fuzzy extraction

A simple and straightforward way of extracting the fuzzy rule base is by mapping all training data using fuzzy theory (Fung et al, 1997). In this method, the analyst will first determine the fuzzy regions, membership functions and fuzzy linguistic labels. After all these have been determined, the available core data are mapped directly to the fuzzy membership functions following the equation:

$$Rn \Rightarrow [x_1^n(A_{t1}, \max), ..., x_k^n(A_{tk}, \max) : y^n(B_t, \max)]$$

where Rn are the fuzzy rules
x^n_k are the input values
(A_{tk}, max) is the membership function with highest degree

This method generates fuzzy rules, enabling analysts to predict petrophysical properties of the wells.

Another method of extracting fuzzy rules directly from input-output data based on clustering has also been applied in reservoir evaluation (Gedeon et al, 2002). The method is to perform fuzzy clustering on the rock types. It is an improvement of the original classification method by Abe and Lan (1995), and the misclassification problem from the original method is solved. The method has been tested on data from the North West Shelf, offshore Western Australia. The method produces 8%–20% improvement over the original Abe and Lan method.

Fuzzy logic can be used for lithofacies prediction based on the fuzzy possibility theory (Cuddy, 2000; Cuddy and Glover, 2002). The fuzzy possibility theory was used to handle the uncertainties in the lithofacies prediction. The prediction is based 'on the assertion that a particular lithofacies type can give any log reading although some readings are more likely than others.' (Cuddy and Glover, 2002), and has been used successfully to perform lithofacies prediction in the North Sea fields. It has been shown by Cuddy and Glover (2002) that their method has a success rate of over 86% compared to a random prediction rate of 13%.

When predicting the permeability of the wells, instead of using data bins assigned to litho-types, the prediction can be achieved by using equal size bins with the use of fuzzy logic (Cuddy and Glover, 2002). The term bins used here has a similar meaning to clusters. The core permeability values are first divided into a number of equal size bins on a logarithmic scale. They are then analysed, the mean and standard deviation of the data in each bin calculated. By knowing the mean and standard deviation of each bin, the fuzzy possibilities that the point lies in that bin are then calculated using:

$$R(x_f) = e^{-(x-\mu_f)^2/2\sigma_f^2}$$

This method has been applied successfully to predict permeability in the Ula Field, 209 km to the southwest of Norway.

Fuzzy rules can also be extracted from to input-output data using Takagi-Sugeno-Kang (TSK) methods (Takagi and Sugeno, 1985; Sugeno and Kang, 1986). When using the TSK fuzzy model, fuzzy rules are extracted to construct the determination model for petrophysical rock properties prediction (Finol and Jing, 2002). The fuzzy rules in the TSK determination model have the following format:

If x_1 is A_{i1} and ... and x_m is A_{im}
Then $y_i = a_{i0} + a_{i1}x_1 + ... + a_{im}x_m$

The two main steps in TSK fuzzy model identification are structure identification and parameter estimation. The fuzzy model used by Finol and Jing (2002) for permeability prediction can be summarised in four steps. They first perform the determination of the input variables by using some prior knowledge. After that, clustering of the data is performed to determine the number of fuzzy rules. Lastly, they set the antecedent fuzzy sets and estimate the consequents of the fuzzy model. This method has been successfully applied to the Lake Maracaibo Basin.

Hierarchical fuzzy system

As the number of well logs increases in the determination model, the complexity of the fuzzy model increases exponentially. There are two problems when dealing with complex systems whose number of input variables is large. Firstly, fuzzy rule bases suffer from rule explosion. The number of possible rules necessary is $O(T^k)$ where k is the number of input variables and T is the number of fuzzy terms per input variable. The second problem is the loss of interpretability of fuzzy rules. Hierarchical fuzzy systems may be used as a better alternative to the rule explosion problem (Chong et al, 2002). The general idea of the hierarchical fuzzy system is based on the theory discussed by Kóczy (1993). Often, the multi-dimensional input space $X = X_1 \times X_2 \times \ldots \times X_k$ can be decomposed into some subspaces, e.g. $Z_0 = X_1 \times X_2 \times \ldots \times X_{k0}$ $(ko < k)$, so that in Z_0 a partition $P = \{D_1, D_2, ..., D_n\}$ can be determined. In each D_i, a sub-rule base R_i can be constructed with local validity. Chong et al (2002) have shown that their hierarchical fuzzy system can be used for petrophysical properties prediction.

Fuzzy rules interpolation

All the fuzzy modelling techniques discussed so far suffer from one problem, namely that the fuzzy rule base extracted is sparse. In the case where a fuzzy rule base contains gaps, which is a sparse rule base, classical fuzzy reasoning methods can no longer be used. This is due to the lack of inference mechanisms in the case where observations find no fuzzy rule to fire. Fuzzy rule interpolation techniques provide a tool for specifying an output fuzzy set whenever at least one of the input spaces is sparse. Kóczy and Hirota (1993) introduced the first interpolation approach known as (linear) KH interpolation. This method determines the conclusion by its α-cuts in such a way that the ratio of distances between the conclusion and the consequents should be identical with that among observation and the antecedents for all important α-cuts (breakpoint levels). This is shown in the equation as follow (see figure 4 for notations):

$$d(A^*, A_1) : d(A^*, A_2) = d(B^*, B_1) : d(B^*, B_2)$$

where A^* is the observation of the input
A_1 and A_2 are the neighbouring fuzzy memberships of the observation
B^* is the interpolated output for A^*
B_1 and B_2 are the neighbouring fuzzy memberships used to interpolate the B^*

The use of fuzzy rule interpolation for multi-dimensional input spaces has been examined by Wong et al (2000) and applied successfully in petrophysical properties prediction by Wong and Gedeon (2001). The method can be used to interpolate the gaps between the rules. This ensures that the set of sparse fuzzy rules generated by any fuzzy rule extraction technique will be usable in a practical system. The fuzzy rule interpolation technique enables any fuzzy model containing a sparse fuzzy rule base to be able to perform petrophysical properties prediction, at the same time without increasing the number of fuzzy rules.

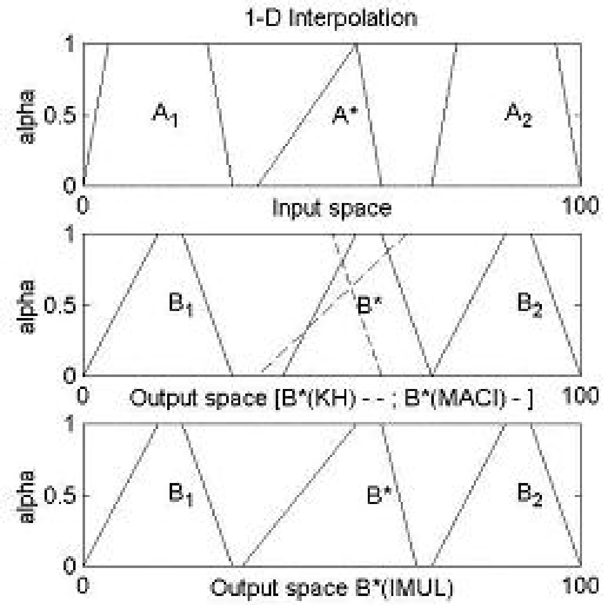

Figure 4. Fuzzy rule interpolation

Fuzzy pre-processing and post-processing

Besides using fuzzy logic in establishing the model itself, it is also used in some cases as a pre-processing or post-processing tool. Pre-processing and post-processing is necessary to ensure the quality of the available data used to establish the determination model, and the quality of the predicted values from the determination model. As analysts normally use some heuristic rules to determine the quality, it is suggested that fuzzy rules can used to perform this task automatically and easily (Wong K.W. et al, 2002). Wong et al created the fuzzy pre-processing or post-processing rules by using some initial knowledge of the well responses from the analyst. Before the input-output data are used to establish the determination model, they are input to the fuzzy pre-processing fuzzy rule base for validation. Data that are found to violate the heuristic rules is discarded and reported to the analyst. The analyst can then decide whether it is a noisy data point which should be excluded in building the determination model. In the post-processing stage, when any prediction output is found to violate the heuristic rules, it will be reported to the analyst. In this case, the analyst can then examine the determination model or the training data to find the cause of this violation. Another way of using fuzzy theory in pre-processing is to use it as a fuzzy ranking (Weiss et al, 2002). Fuzzy ranking can be used to analyse noisy data sets and thus improve the overall determination process. Fuzzy theory can also be used to transform the target petrophysical properties to linguistic classes to improve the accuracy of an intelligent determination model (Wong P.M. et al, 2002). In the pre-processing stage, they transform the target outputs into linguistic classes that are in the form of fuzzy membership functions. A conventional neural network is then used to predict the membership function values. After the prediction is made, simple post-processing of the outputs transform the values back to its original form with confidence bounds.

CONCLUSIONS

This paper has given a review of the application of fuzzy theory and fuzzy systems used in reservoir evaluation. There are a few techniques that have been successfully applied to this field in extracting fuzzy rules from the input-output data. The main challenge in this area is to ensure that the fuzzy rule extraction techniques can obtain a set of fuzzy rules that can generalise the underlying function of the determination model. The desirable features of fuzzy systems include the ability to handle noisy data, ability to handle missing information, ability to perform feature selection efficiently, and the ability to present a fuzzy rule set that can be understood by the analyst. As the number of fuzzy rules is directly dependent on the number of input logs and the number of membership functions, the desirable features in hierarchical fuzzy systems such as those described by Chong et al (2002) can also be further explored. This paper is a concise overview and can act as a guide for petroleum engineers to take advantage of the advanced fuzzy logic technologies in practice, as well as for performing research in this field.

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APPEA

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