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A self-generating fuzzy rules inference system for petrophysical properties prediction

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Abstract – **This paper report the application of a self-generating fuzzy rules extraction and inference system for the prediction of petrophysical properties from well log data. A set of core data with known characteristics is first selected as the training samples. Fuzzy rules are then extracted and undergone a process of rule elimination. The reduced rule set forms the rule-base of the fuzzy prediction model. This will be used to predict properties of other depths within or around the well. Results based on a test case for the prediction of porosity is reported and the performance of the system is discussed.**

1. INTRODUCTION

In petroleum well modeling, boreholes are drilled at different locations around the region. Well logging instruments are lowered into the borehole to collect data at different depths known as well log data. Well logging instruments used in the measurement of well log data broadly fall into three categories: electrical, nuclear and acoustic [1]. Examples are Gamma Ray (GR), Resistivity (RT), Spontaneous Potential (SP), Neutron Density (NPHI) and Sonic interval transit time (DT). There are over fifty different types of logging tools available for different requirements. Beside the well log data, samples from various depths are also obtained and undergo extensive laboratory analysis. These laboratory analysis data is known as core data in well log analysis process. In well log analysis, the objective is to establish an accurate interpretation model for the prediction of petrophysical characteristics such as porosity, permeability and volume of clay for uncored depths and boreholes around that region [2,3]. Such information is essential to the determination of the economic viability of a particular well or region to be explored. Although empirical formulae relating well log data to the petrophysical properties may be used, the unique geophysical characteristics of each region prevent a single formula to be applicable universally. Instead, statistical techniques and graphical methods are used extensively. To ensure validity of the model, core data from particular wells are undergone detailed analysis and serve as references. Parameters of the model are then manipulated in order to match the overall output to the core data. This expected that this would result in a better model and increase the overall accuracy.

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However, with the availability of increasing number of instruments and log data, it becomes difficult to apply the traditional statistical and graphical methods. To overcome the problem, alternative techniques such as Artificial Neural Networks (ANN) have been applied. Results of these works have been reported in the past few years. Most of the ANN applications are based on the Backpropagation Neural Networks (BPNN) [4,5,6] which make use of core data as training samples. Once the network is trained, it is used as a model to predict subsequent inputs at different depths or boreholes around that region. Although applications of neural networks have been successful, disadvantages such as long training time and the need of appropriate training parameters have caused inconveniences in practical use. In addition, once the network is trained, the model is seen as a black box and the user has no access to any explicit knowledge that the network has learn. Finally, from user's viewpoint, it is also very difficult to manipulate the neural network model and inability to include any prior knowledge.

In this paper, a fuzzy-rule-based petrophysical properties prediction system is proposed. It uses an automatic self-generating fuzzy rules extraction and inference system [7] to establish an interpretation model. The fuzzy rules are first extracted from the available core data. The rules are then processed and reduced. Then they form the knowledge base for the prediction of subsequent data. With this proposed self-generating fuzzy rules inference system, the interpretation model can be established easily and quickly. As the training only involve a one-pass rule extraction, the training time for this system is very short. The analyst also does not need to have extensive knowledge of the fuzzy system in order to build the interpretation model. The final interpretation model will comprise of fuzzy rules that the analyst can understand and modify them. The user can also add on their experience and knowledge into the fuzzy rules base with ease. As compared to the BPNN training, its training process is fast and simple. The analyst has the ability to include human knowledge and manipulate the interpretation model. This is a distinct advantage over the black-box approach as in the neural network method. Results from the case study have also shown that it can provide promising prediction with short training time and human understandable fuzzy rules.

2. SELF-GENERATING FUZZY INTERPRETATION SYSTEM

The objective of this self-generating fuzzy system is to aid the user in setting up a fuzzy rules interpretation model by mapping the available core data to their corresponding memberships. After which has been done, the user can examine the interpretation model from the fuzzy rules. The user can then modify and add-on to the rule base easily. The fuzzy interpretation model is established in the following steps:

(1) Normalise the data between 0 and 1 by using linear or logarithmic transformation depending on the nature of the well log data. This is to ensure that the resolutions of all data are similar.

(2) Define the shape of the membership function, number of fuzzy regions and fuzzy terms for all data.

In this paper, only triangular type of membership function is used. The number of the fuzzy regions used is the same for all inputs and output. Fuzzy terms used in this paper is in the form as L is low, M is medium and H is high. An example of a five fuzzy region term is:

VL, L, M, H, VH.

(3) The space associated with each fuzzy term over the universal discourse for each variable is then calculated and divides them evenly. For example a value with range between 0 and 1 with 5 membership-terms is shown in Figure 1.

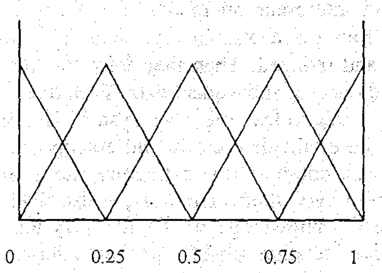

Figure 1: Distribution of 5 membership-terms

(4) For each available core data, a fuzzy rule is established by directly mapping the physical value of the variable to the corresponding fuzzy membership function.

Most of the time for a given value, it will normally fall into more than one fuzzy region. In this case, a degree is given to that value in the fuzzy region. The value is then assign to the fuzzy region with maximum degree.

(5) Go through Steps (4) with all the available core data and generate one rule for each input-output core data pair.

(6) Reduced the fuzzy rule base.

In this step, all rules are examined for similarity. Similar rules are then eliminated and taken from the rule base.

(7) The set of reduced fuzzy rules together with the centroid defuzzification algorithm now forms the fuzzy interpretation model.

After the fuzzy-rule interpretation model has been set up, it can then be used to predict any unknown data coming in. With the fuzzy interpretation model being set up, based on the analyst's experience, the rules may be manipulated explicitly to incorporate human knowledge and experience.

3. CASE STUDY

A case study has been used to illustrate the application of this proposed approach. Well log data from two typical wells are used to predict the petrophysical property, porosity (PHI). Core data from one well are used to establish a prediction model based on the proposed self-generating fuzzy rules inference system. The model is then used to predict the porosity of the second well. The input logs used in this case study are gamma ray (GR), deep induction resistivity (ILD) and sonic travel time (DT) and all the variables are normalised between the values of 0 and 1. The first well has a total of 71 core data and is used as the training well. The second well has 51 core data and is used as the testing well to test the prediction accuracy of the trained fuzzy interpretation model.

A few test cases are carried out to see the effect of the number of membership. The numbers of rules obtained by varying the number of memberships are shown in Table 1. The rules extraction time for the three cases vary from 30 sec to 1 min based on a Pentium 90 Personal Computer. Results showed that the number of fuzzy rules increases with the number of membership term. The prediction accuracy for both training and testing wells in each test case is tabulated in Table 2. It can be observed from Table 2 that the results obtained from the self-generating fuzzy rules inference system have high correlation to the original core data. Figures 2 and 3 are the output plots from the 9 memberships fuzzy inference system for the training and testing wells respectively. Figure 4 shows a section of the fuzzy rules extracted from the core data after rule elimination using 5 membership. Figure 5 shows the fuzzy membership function for the 5 memberships fuzzy inference system.

Table 1: No. of rules generated for each case.

No. of membership	No. of rules extracted
5	29
7	46
9	63

Table 2: Prediction accuracy for each case.

No. of membership	Training Correlation	Testing Correlation
5	0.805	0.792
7	0.889	0.853
9	0.917	0.865

From the results, the fuzzy interpretation model can generate promising prediction. The time taken in setting up the fuzzy interpretation model is also very short. With the understanding of the membership function as those in Figure 5, the rules can be examined and modified. As the raw data has been first normalised between 0 and 1, the membership functions of all the input and output variables will be similar as those shown in Figure 5. This again enables the analyst to easily understand all the fuzzy terms regardless of the number of input and output variables.

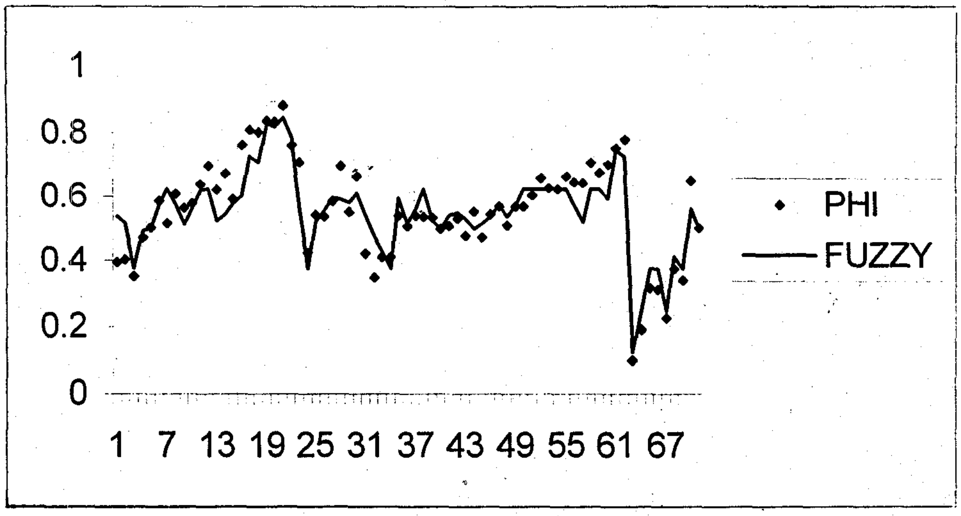

Figure 2: Output plot of TRAINING well using 9 membership functions.

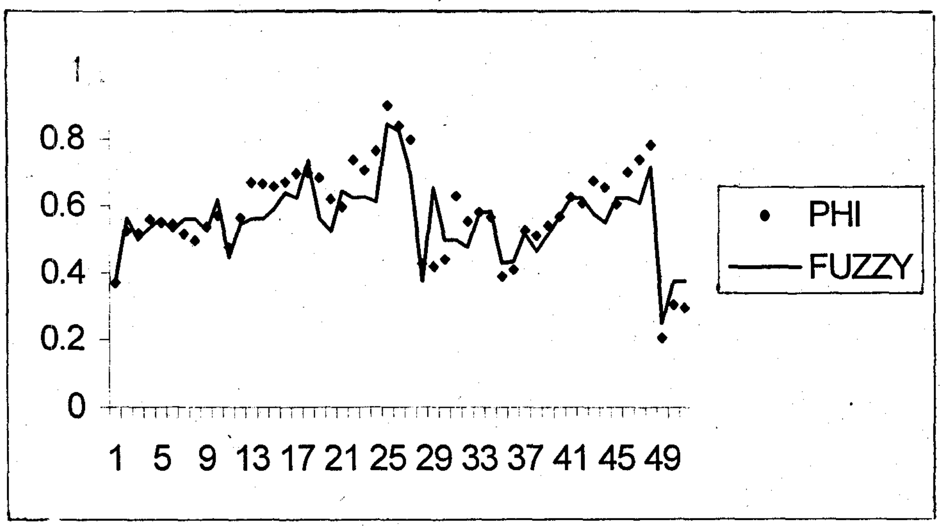

Figure 3: Output plot of TESTING well using 9 membership functions.

If GR = h and ILD = l and DT = h then PHI = m
If GR = h and ILD = vl and DT = m then PHI = l
If GR = m and ILD = vl and DT = h then PHI = m
If GR = h and ILD = vl and DT = h then PHI = m
If GR = vh and ILD = vl and DT = h then PHI = m
If GR = vh and ILD = l and DT = h then PHI = m
If GR = h and ILD = l and DT = h then PHI = h
If GR = h and ILD = l and DT = vh then PHI = h
If GR = vh and ILD = l and DT = vh then PHI = h
If GR = m and ILD = m and DT = m then PHI = m

Figure 4: Section of rules for 5 membership fuzzy system.

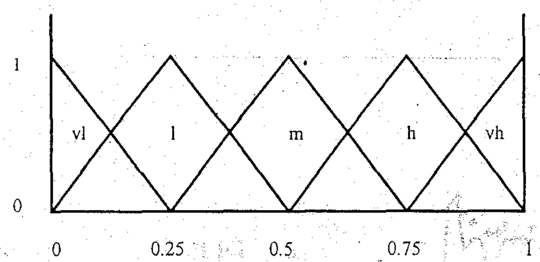

Figure 5: Fuzzy terms and regions for 5 memberships fuzzy inference system.

4. CONCLUSION

This proposed fuzzy interpretation model used to predict petrophysical properties has proven to be promising. It makes use of the available core data to build the fuzzy rules base, and performs a one-pass operation that requires very short training time. The user does not need to have extensive knowledge of the fuzzy system in order to build the interpretation model. The set of rules describes explicitly the knowledge embedded of the training data. Additional human knowledge or core data can be added to the rule base easily and quickly, without the need of re-training. The final fuzzy interpretation model can be used to integrate knowledge extracted from the core data as well as prior experience of the user. This approach is more meaningful and useful to the analysts.

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