Prediction Model of Permeability From Well logs Using Type-2 Fuzzy Logic Systems

Sunday Olusanya Olatunji
(s.o.olatunji@gmail.com, oluolatunji.aadam@gmail.com)
Intelligent Software Engineering Laboratory, Faculty of Computer Science & Information Systems, Universiti Teknologi Malaysia, 81310 UTM Skudai, Johor, Malaysia

Ali Selamat
(aselamat@utm.my)
Intelligent Software Engineering Laboratory, Faculty of Computer Science & Information Systems, Universiti Teknologi Malaysia, 81310 UTM Skudai, Johor, Malaysia

Abdul Azeez Abdul Raheem
(toazeez@gmail.com)
Centre for Petroleum and Minerals, The Research Institute, King Fahd University of Petroleum and Mineral, Dhahran 31261, Kingdom of Saudi Arabia

Abstract: In this paper, the viability and capability of using Type-2 Fuzzy Logic Systems as a novel approach for predicting permeability from Well Logs has been investigated and implemented. Type-2 fuzzy logic is powerful in handling uncertainties, including uncertainties in measurements and data used to calibrate the parameters. In the formulation used, the value of a membership function corresponding to a particular permeability value is no longer a crisp value; rather, it is associated with a range of values that can be characterized by a function that reflects the level of uncertainty. In this way, the model will be able to adequately account for all forms of uncertainties associated with predicting permeability from well log data, where uncertainties are very high and the need for stable results are highly desirable. Comparative studies have been carried out to compare the performance of the proposed framework with those earlier used methods, using real industrial reservoir data. Empirical results from simulation show that Type-2 FLS approach outperforms others in general and particularly in the area of stability and ability to handle data in uncertain situations, which are the common characteristics of well logs data. Another unique advantage of the newly proposed model is its ability to generate, in addition to the normal target forecast, prediction intervals as its by-products without extra computational cost.

Keywords: Permeability estimation, Well logs, Type-2 fuzzy logic systems, reservoir characterization, Support Vector Machines, Feedforward Neural Networks

I. INTRODUCTION

Permeability is one of the most important of reservoir properties, and their prediction has been one of the fundamental challenges to petroleum engineers and researchers [1]. Accurate knowledge of Permeability property is required to determine the amount of oil or gas present in reservoirs, the amount that can be recovered, the flow rate of oil or gas, the forecast of future production, design of production facilities, and for the overall reservoir management and development requires accurate knowledge of permeability [1, 2]. Permeability, or flow capacity, is the ability of porous rock to transmit fluid [3]. Although a rock may be very porous, it is not necessarily very permeable. Permeability is the ease with which fluid is transmitted through a rock's pore space**.** It is a measure of how interconnected the individual pore spaces are in a rock or sediment.

The recent success of applying artificial neural networks (ANN) to solve various engineering problems has drawn the attention to its potential applications in the petroleum industry. Thus, an alternative approach to the parametric modeling approach is the application of artificial neural networks (ANNs). In attempt to resolve problems associated with the parametric approach, the standard artificial neural networks (ANNs) have been used to provide better prediction models [13-16]. These works yielded a significant prediction improvement in the oil and gas industries. See [17-24] for further works carried out in this direction. However, the technique still suffers from several drawbacks. These shortcomings include the trial-and-error approach of ANN, the need to guess its architectural parameters in advance, such as, number and size of hidden layers and the type of transfer function(s) for neurons in the various layers. Moreover, the training algorithm parameters were determined based on guessing initial random weights, learning rate, and momentum. Although acceptable results may be obtained with effort, it is obvious that potentially superior models can be overlooked. Most importantly, ANN suffers from instability in its predictions and it is unable to model uncertainties, which characterize well logs in particular.

Researchers in both machine learning and data mining communities did their best to address and overcome these problems of ANN. As a result, several variants of ANN and other methods like support vector machines (SVM) and functional networks (FN) have been proposed and used [4, 12, 24], yet each has its limitations that still call for further research of this nature, particularly their inability to handle uncertainties and the need to ensure stability in permeability predictions. Recently, Type-2 Fuzzy Logic Inference Systems have been proposed as new intelligence frameworks for both prediction and classification to handle all forms of uncertainties [26-29]. Type-2 fuzzy logic is powerful in handling uncertainties, including uncertainties in measurements and data used to calibrate the parameters. It has since featured in a wide range of medical, business and engineering applications, often with promising and stable results [30-36]. Therefore, bearing in mind the fact that there is uncertainty in reservoir characteristics and well log data, it becomes clear that the best way to tackle this problem of uncertainty is to make use of type-2 fuzzy logic; which is an approach that has been specifically invented to deal with all forms of uncertainty [26] that is inherent in our day to day natural encounters and mode of reasoning. Thus the significance of type-2 fuzzy logic based prediction model, hereby proposed, cannot be overemphasized.

The main objectives of this study are (1) to investigate the feasibility of type-2 FLS in forecasting permeability; (2) to develop a new intelligence framework, based on type-2 FLS, for predicting permeability from well logs using real industrial well log data; (3) to investigate how various earlier commonly used standard neural network, support vector machines and functional networks compare in their performance in predicting permeability of carbonate reservoirs; and (iv) to explore how type-2 FLS framework can generate prediction intervals, permeability, effortlessly as its by-product.

II THE PROPOSED TYPE-2 FUZZY LOGIC SYSTEM INTELLIGENCE FRAMEWORK

In this work, type-2 fuzzy logic framework is presented and utilized for predicting permeability from well log data based on distinct real-world industrial data. The goal is to completely specify the FLSs using the training data, which is a unique characteristic of adaptive fuzzy systems. Type-2 Adaptive Fuzzy Inference Systems (ANFIS) is an adaptive network that learns the membership functions and fuzzy rules, from data, in a fuzzy system based on type 2 fuzzy sets, see [26, 37] for details. “Type-2 fuzzy sets are fuzzy sets whose grades of membership are, them-selves, fuzzy. They are intuitively appealing because grades of membership can never be obtained precisely in practical situations” [38]. The fuzzifier takes the well log input parameters values as inputs. The output of the fuzzifier is the fuzzified measurements which will be the input to the inference engine. The resultant of the inference engine is type-2 fuzzy output sets which can be reduced to type-1 fuzzy set by the type reducer. This type reduced fuzzy set in this model is an interval set which gives the predicted external attribute measurement as a possible range of values. The defuzzifier calculates the average of this interval set to produce the predicted crisp external attribute measurement (which is the permeability values).

1. Initializing the Framework

To initialize the framework, we need to define the components of a typical type-2 fuzzy logic system from the perspective of permeability model. In this work, we initialized FLS from the numerical dataset. In this model, we have the antecedents and consequents: (1) internal attributes are the antecedents, which in this case are the well log variables, (2) external attribute is the consequent which is the permeability value to be predicted in this case. To initialize the framework, we make use of training data set created from the available measurement data. The proposed model required that the antecedent and consequent membership functions be considered as type-2 Gaussian with uncertain mean (m) and the input membership functions will be type-2 Gaussian with uncertain standard deviation (σ) as shown below.

$$\mu_A(x) = \exp\left[-\frac{1}{2}\left(\frac{x-m}{\sigma}\right)^2\right] \quad m \in [m_1, m_2]$$

Corresponding to each value of m, there will be a different membership curve as shown in figure 5.

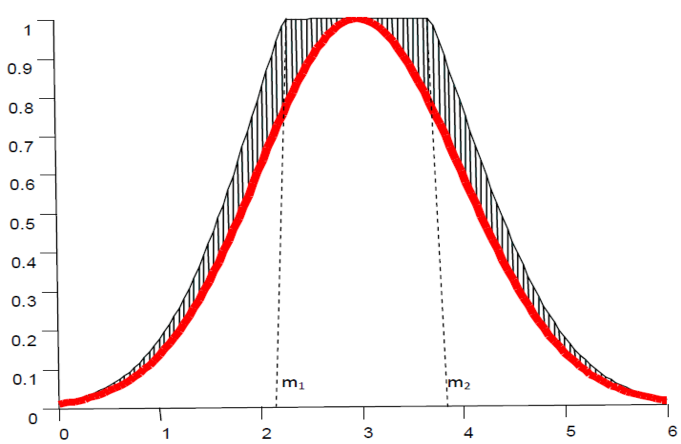

FIGURE 1: Foot print of uncertainty (FOU) for Gaussian primary membership function with uncertain mean.

$$\mu_A(x) = \exp\left[-\frac{1}{2}\left(\frac{x-m}{\sigma}\right)^2\right] \quad \sigma \in [\sigma_1, \sigma_2]$$

Corresponding to each value of σ, there will be a different membership curve as shown in figure below.

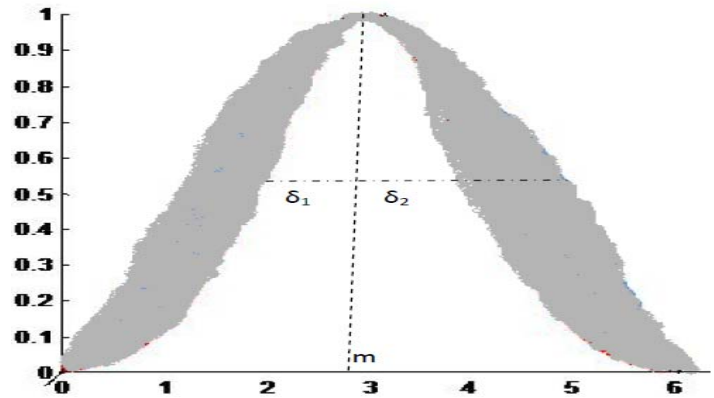

FIGURE 2: Foot print of uncertainty (FOU) for Gaussian primary membership function with uncertain standard deviation.

The uniform shading for the foot print of uncertainties (FOU), in the two figures above, again denotes interval sets for the secondary membership function and represents the entire interval type-2 fuzzy set $\mu_{\tilde{A}}(x,u)$.

Sample rule for the framework looks like;

$$R^i: IF\ x_1\ is\ F_1^i\ and\ x_2\ is\ F_2^i ... and\ x_P\ is\ F_P^2\ THEN\ y_i\ is\ G^i$$

From the above rules, for the consequent part, R^i represent the i[th] type-2 fuzzy rule for the i[th] sample, F_1^i is a fuzzy set whose membership function is centered at the 1[st] attribute of the i[th] sample. For the consequent part, G^i is a fuzzy set whose membership function is centered at target output y of i[th] sample.

For a further detail explanation of various ways to initialize and train type-2 FLS, see [26].

2. Training the Model with Adaptive Type-2 Fuzzy Learning Process

After initializing the FLS, part of the available dataset will be used as training data. It will contain the input-output pair where the inputs are independent variables and the output is the target attribute. Our training procedure follow strictly type-2 fuzzy logic standard, details of which can be found in [26, 29]. Figure 3 depicts the proposed type-2 adaptive fuzzy inference system network. The network depicted has a number of parameters to be learnt. Firstly there are parameters for the membership grades of the antecedent type 2 fuzzy sets in layer 1. Layer 3 has the consequent type 2 fuzzy sets and there are parameters to be learnt there as well. Since the output of the network is numeric this can be compared with the expected output from a teacher (i.e. supervised learning) and back propagation used to feed the error back to adjust the parameters in the nodes. For illustration purposes, the method for two inputs is discussed but this is extendable. GR and RT are vectors representing well log inputs (Gamma Rays and Resistivity respectively) that might have different representations for different type 2 fuzzy sets while Perm denote the final permeability output from the system.

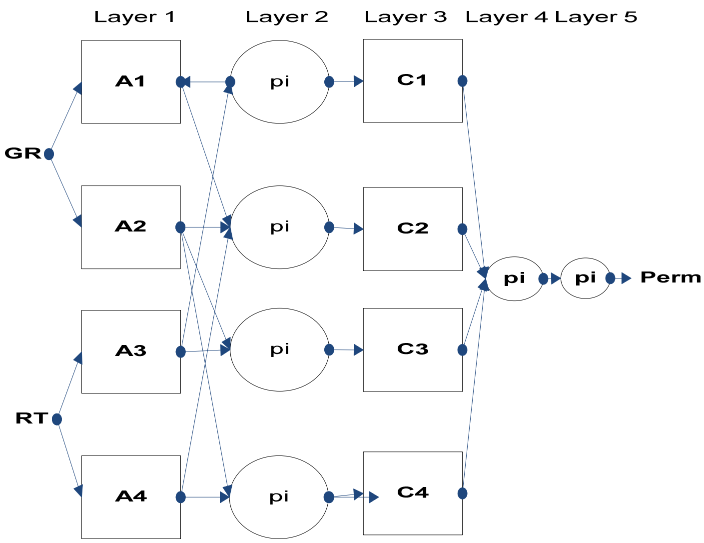

FIGURE 3: A type-2 adaptive neuro-fuzzy inference system network.

The grades in type-2 sets are actually fuzzy numbers, that is, rather than a membership grade being crisp in [0, 1] it's a fuzzy number in [0,1] where the width of the set indicates the uncertainty attached to the number. For a two input, one output model there can be four fuzzy rules as follow:

IF GR is A1 and RT is B1 THEN Z is C1
IF GR is A1 and RT is B2 THEN Z is C2
IF GR is A2 and RT is B1 THEN Z is C3
IF GR is A2 and RT is B2 THEN Z is C4,

where A1, A2, B1, B2, C1, C2, C3, C4, are type 2 fuzzy sets. The network in figure 3 describes the type-2 fuzzy system encoded in the rules above. A square node indicates an adaptive node with modifiable parameters whereas a circle indicates a fixed node that simply performs a function.

III EMPIRICAL WORK, DISCUSSION AND COMPARATIVE STUDIES

In order to carry out empirical study, two distinct real-industrial databases (Well-W1 with 356 data points and Well-W2 with 478 data points) were acquired having well log inputs parameters that include Wire line logs from these wells included CT (electrical conductivity), DRHO (density), DT (sonic travel time), MSFL (Micro spherically Focused Log), NPHI (Neutron porosity), PHIT (total porosity), RHOB (bulk density), RT (Resistivity), and SWT (water saturation). One important additional benefit of type-2 FLS worth mentioning at this point is that, compared with earlier used models, the proposed type-2 FLS will generate not only the permeability predictions, but also prediction intervals effortlessly as its by-product. It achieved this through its type-reduction process that generates the intervals as the by-product. See,[26], for further details. A sample permeability prediction intervals generated in this work is shown in figure 4. This, indeed, is another great contribution of this work.

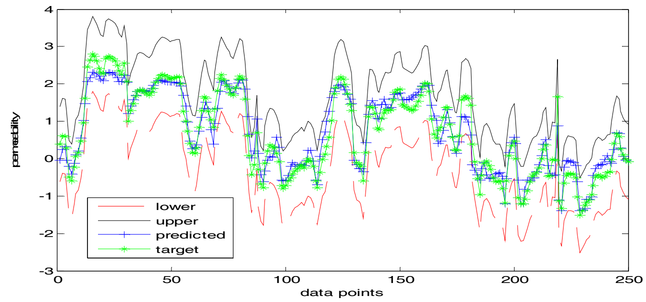

Figure 4: Permeability prediction intervals based on Type-2 FLS

IV CONCLUSION AND RECOMMENDATION

In this study, two distinct industrial data set were made used of in investigating the feasibility, performance, and accuracy of the proposed type-2 FLS based modeling scheme as a new framework for predicting the permeability from well log. A new computational intelligence modeling scheme, based on the type-2 fuzzy logic system has been investigated, developed and implemented, as predictive solution, that takes care of all forms of uncertainties, for predicting permeability from well logs. Validation of the framework is done using real industrial well log data. In-depth comparative studies have been carried out between this new framework and the standard neural networks, support vector machines and functional network. Empirical results from simulations show that the proposed model outperformed all the compared models in all fronts. Based on the published literature to date, it can be said here that, for the first time in the history of permeability predictions, this work has presented a Type-2 FLS based model that will generate not only the target permeability forecast but also prediction intervals without effortlessly. As a form of future work recommendations, it is suggested that other models like that of porosity, history matching, lithofacies and other reservoir engineering properties could be built using this framework. Also more dataset could be considered while investigating the effect of absence or presence of preprocessing techniques.

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