TECHNICAL MEMORANDUM

PREDICTION OF LITHOFACIES AND ROCK PROPERTIES FROM OIL WELL LOG DATA USING ABDUCTIVE NETWORK MACHINE LEARNING

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SUMMARY

This Technical Memorandum proposes the use of abductive network machine learning modeling techniques for the identification of rock lithofacies and prediction of their physical properties from well log data. This provides useful information needed for reservoir characterization using only a limited amount of core data. Models constructed from data on logged and cored well intervals will be used to predict rock properties in logged but un-cored intervals and possibly for logged but un-cored adjacent wells. The proposed machine learning technique offers a number of advantages compared to neural networks used recently for this purpose. These include: Simplified and automated model synthesis requiring less user intervention, and analytical input-output relationships that highlight significant input parameters and give better insight into the modeled physical phenomena.

The work proposed should be of benefit to many clients in the area of oil and gas exploration and production and the associated disciplines of data processing and analysis. It allows extraction of useful information on lithofacies classification and rock properties from readily available log data; thus reducing the cost and effort of extracting and laboratory-testing of core samples.

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SECTION 1 INTRODUCTION

Identification of lithofacies types (e.g. sandstone and mudstone), and determination of rock physical properties (e.g. porosity and permeability), are important aspects of characterizing complex geological formations, estimating reserves, forecasting production, and planning enhanced recovery operations for oil reservoirs. Laboratory measurement of such parameters is possible using core samples extracted at the required depths. However, well bore conditions are not always favorable and the process is tedious and expensive, making it practical only at selected wells and depth intervals. An easier process is to log the well using electronic equipment to measure and digitally record a number of parameters such as rock density, sonic travel time, neutron backscatter, and natural gamma-ray emission.

Rock parameters of interest at un-cored locations can be estimated by interpolating/extrapolating the relationship between the log data and the corresponding available core measurements to other intervals of a cored well or even to other un-cored well in the same field. However factors that contribute to the difficulty of this task include the complex, non-linear and often unknown relationships involved, the inherent variability and incompleteness of the log data due gradations in rock characteristics, effects of data acquisition, and statistical fluctuations in radiation log measurements.

Modern computational intelligence and machine learning modeling approaches promise solutions to many of the problems encountered with conventional modeling techniques. This memorandum proposes the use of an abductive network machine learning method which has proved effective in a number of similar applications.

SECTION 2 OBJECTIVES

We propose applying abductive network machine learning techniques to the important area of modeling and predicting lithofacies and physical rock properties in un-cored well regions from well log data which are more readily available. A data base consisting of an adequate number of solved examples will be used to develop and evaluate the model. The data base should include log data as inputs and the output parameters to be modeled, as determined from laboratory tests on core samples extracted at corresponding depths. The model synthesized is then evaluated on a sub set of the data reserved for this purpose and not used previously for training. The model is validated through examining its performance on this evaluation data set. The proven model can then be put to actual use in predicting the modeled parameters in well regions where no core data exist. Use of a model derived from one well to predict parameters for a different adjacent well will be investigated due to its important practical applications. Work involves coordination with the client in preparing a suitable data base and performing data pre-processing to ensure good quality of the training and evaluation data, model synthesis through supervised learning, model evaluation, and documentation. Performance will be compared with conventional and other computational intelligence approaches reported in the literature.

SECTION 3 DISCUSSION OF THE PROBLEM

3.1. Description of the Problem

Traditionally, theoretical relationships [1], empirically determined models [2], and statistical multiple linear regression (MLR) analysis [3] have been used to estimate rock properties in un-cored intervals of oil wells. The theoretical approach; e.g. the Kozeny-Carmen theory relating permeability to porosity, tends to oversimplify the behavior of the very complex porous media [4]. In addition to the difficulty in deriving a representative empirical relationships, results apply only to limited regions [5], and suffer from poor generalization [6]. With MLR, the fundamental assumption of a linear relationship between the modeled parameter and the well logs limits the usefulness of the technique [7]. A recent trend in handling such difficult problems has been to resort to artificial intelligence and machine learning techniques such as neural networks, fuzzy logic, and genetic algorithms. With this approach, a model for the phenomenon considered is automatically developed through training on an adequate number of solved examples. Once synthesized, the model can be used to perform fast predictions of outputs corresponding to new cases previously unseen during training. The method offers a number of advantages over conventional approaches, including increased tolerance to noise and reduced need for knowledge on the relationships being modeled.

Statistical classifiers such as discriminant analysis have been used to classify lithofacies types [8]. However, the technique suffers from limitations due to the assumption of a statistical normal distribution for the variables, particularly when the training set is small [9]. Moreover, since only discrete variables are supported, the method can not be used to predict analog values of rock properties. Various forms of neural networks have been used to identify lithofacies and estimate parameters such as permeability and porosity [10], [11-14]. They achieve better classification accuracy compared to discriminant analysis [9] and make no assumptions on the statistical distribution functions of the variables. However, the commonly used standard back propagation paradigm may require long training times [9] and is sensitive to initial conditions. Moreover, model development with neural networks requires considerable user intervention. The user often has to experiment with various architectures and there are no hard and fast design rules to determine optimum values for the number of hidden layers, number of neurons in each layer, and the training parameters, where a number of trial and error attempts are usually needed in search of the best solution [7,17]. The network may get stuck in a local minimum and therefore is not guaranteed to converge to a good solution [16]. Because the method may be unstable and oscillate between solutions, it may not be clear when to stop [17]. A separate validation data set is sometimes used to stop training in time to avoid over-fitting, which reduces the size of the data set that can be used for actual training [7,17]. With the model embodied in a huge number of weights, no much insight is given into the underlying relationships of the modeled phenomenon. In some geophysical applications, performance of conventional neural networks alone was not adequate and the method had to be combined with other techniques such as fuzzy logic [18] and genetic algorithms [19]. Neural networks paradigms employing the gradient descent approach have been known to produce averaged, smoothed estimates that do not produce local variability of the reservoir permeability [5]. Extreme values were being underestimated or overestimated, rendering results unsatisfactory since fluid flow performance is more sensitive to extreme values rather than averages.

3.2. Proposed Approach

We propose using the alternative modeling approach of abductive network [20] machine learning for the estimation of rock properties from log data. The technique has been successfully used at CAPS in a wide variety of applications, including weather forecasting [21,22], nuclear spectroscopy [23,24], online monitoring of machine vibrations [25], forecasting of energy consumption [26], and medical informatics [27,28]. The method offers the advantages of faster training and more automated and faster model development requiring little or no user intervention. With the model represented as a hierarchy of polynomial expressions, the method gives better insight into the phenomenon being modeled. The technique automatically avoids over-fitting using a criterion for penalizing complexity [20] without requiring a dedicated validation data set; thus leaving more training data for use in model synthesis. This proposal aims at using abductive network machine learning as a tool for modeling and estimating useful parameters in petroleum engineering by integrating well log data and available core measurements.

SECTION 4 STATEMENT OF WORK

The proposed work includes the following tasks:

4.1. Establishing the Data Bases (To be provided by the client)

Data bases for both training and evaluation are required. Prediction performance of the resulting models depends on the size and quality of the training data. Each data record consists of input data and output target data. Input data are derived from well log measurements; e.g. gamma ray, density, sonic, neutron porosity data; as well as depth, and possibly latitude and altitude. Output data specify the corresponding known values for the parameters to be modeled. Outputs representing lithofacies categories; e.g. sand, mud, coal, and cemented, should be determined by experienced geologists for each logged depth. A separate binary (logical) output can be associated with each category to indicate its presence/absence at that depth. It is also possible to represent the litofacies type using a single multi-valued integer variable that represents the dominant type for each training sample. Analog outputs represent values of physical rock properties, e.g. permeability, porosity, and grain density, as determined from laboratory measurements on core samples at the corresponding depth. Genetic models for rock properties will also include known lithofacies information as inputs.

It is desirable to have access to data for a number of different wells. This allows verifying if a model synthesized on one cored well can be used to predict data for another well in the same region. If this proves satisfactory, it can cut on the cost of coring additional wells.

4.2. Data Preprocessing

A number of problems usually exist with the raw log data, making it necessary to exercise some caution in the selection of training/evaluation samples and to introduce some data pre-processing. These include [7,31]:

- Uneven distribution of samples; e.g. more measurements from sandy intervals than from shaly intervals, or uneven distribution with depth. Biased sampling may lead to most of the core data available being for good quality rocks at the expense of low quality ones [5]. To ensure adequate modeling of the various lithofacies types and rock property parameters, the full spectrum of all possible types and values should be represented fairly evenly in the training data set.

- Depth shifts may exist between the log data and core data. These must be detected and removed.

- Different spatial resolution between well logs and core tests as they measure different volumes of rock. This limitation may be overcome by incorporating adjacent log responses or averaging of core data [5].

Much of the success with applying classification/prediction algorithms is attributed to the analysis and preparation of the input data prior to training. Common pre-processing techniques often employed with neural network modeling include:

1. Removing bad data points forming outliers. These may result from fractured cores samples or log data being distorted at locations exhibiting rapid lithofacies transitions (thin-bedding, shoulder effects) [9]. It was observed that the reliability of log-predicted permeability derived using a variety of modeling techniques suffered considerably at such locations [4]. Other sources of noise in the training data include uncertain depth matching and variations in core testing conditions.

2. Normalizing the data variables to a unified range, usually based on the minimum and maximum values of the log and core data [9].

3. Using the log scale for some parameters such as permeability before modeling [9]. This was found to reduce training time and improve prediction accuracy of a permeability neural network model that uses lithofacies, log data, and porosity as inputs [9].

4. Excluding input variables that degrade or do not effectively contribute to the desired discrimination or prediction. This cuts on the network training time and reduces dimentionality of the input variables; thus reducing model over fitting for a given size of the training set. For a neural network lithofacies classifier, histograms of the gamma-ray (γ) and the deep induction resistivity (ILD) logs for separate lithofacies in the training data set showed considerable overlap and therefore the two variable were excluded from the training set due to their weak discriminating power [9]. Selecting the most significant input variables can be based on the magnitude of the correlation coefficient with the output quantity, through fuzzy logic ranking [30], or using principal component analysis (PCA) [31].

5. Utilizing available knowledge on the modeled phenomenon to introduce new variables that may improve discrimination/prediction. For instance, in the example in item 4 above,

introducing the acoustic impendence input variable IMP as the ratio between the bulk density (RHOB) and the sonic travel time (DT) improved training time and classification accuracy [9]. The newly generated variable proved to have a larger average contribution to the output than the original two variables.

6. Classification accuracy could be improved by transforming the input training data into a new feature space of lower dimentionality that maximizes linear separation between classes [31].

4.3. Model Development

Records constituting about 70% of the total data for a given well are randomly selected for use in synthesizing an abductive network model that describes the input-output relationship. A model is synthesized for each variable declared as 'output'. The remaining 30% of the data would be reserved for model evaluation.

Abductive network models take the form of layered feed-forward networks of functional elements (nodes) [20]; see Figure 1. Elements in the first layer operate on various combinations of the independent input variables (x's) and the single element in the final layer produces the predicted output for the dependent variable y. Both the element type and the combination of inputs to it from all the previous layers are selected automatically for best prediction performance.

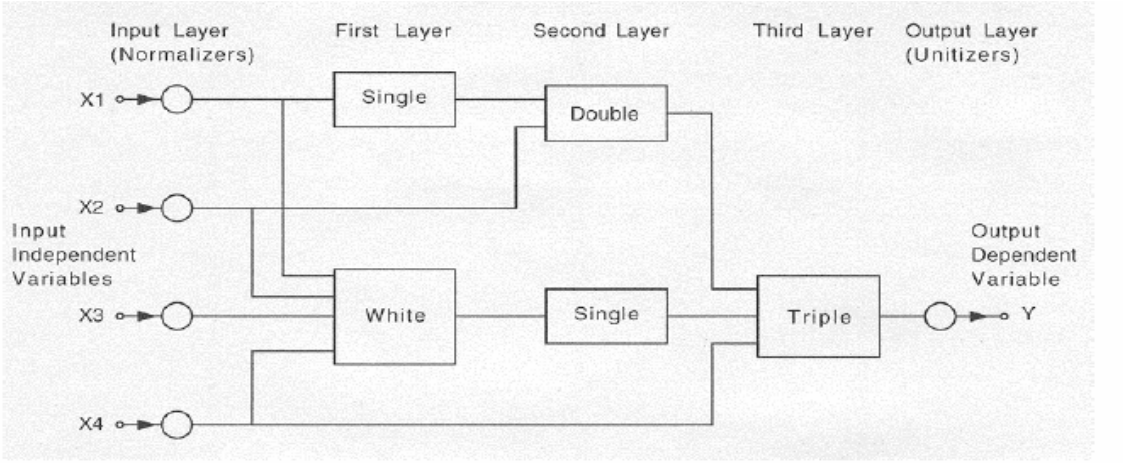

Figure 1. A typical abductive network model showing various types of functional elements

The following main functional elements are supported:

(i) A white element consisting of a constant plus the linear weighted sum of all outputs of the previous layer, i.e.:

"White" Output $= w_0 + w_1x_1 + w_2x_2 + w_3x_3 + ... + w_nx_n$

where x_1, x_2,..., x_n are the inputs to the element and w_0, w_1,..., w_n are the element weights.

(ii) Single, double, and triple elements implementing a 3rd-degree polynomial expression with all possible cross-terms for one, two, and three inputs respectively; for example,

"Double" Output = $w_0 + w_1x_1 + w_2x_2 + w_3x_1^2 + w_4x_2^2 + w_5x_1x_2 + w_6x_1^3 + w_7x_2^3$

This allows taking into account nonlinear combinations of the input variables automatically as required. Using neural networks to predict porosity [6], nonlinear components such as x_1^2 had to be introduced manually. Substituting equations of the various functional elements gives a polynomial expression relating the modeled output parameter to the input variables.

4.4. Model Evaluation and Analysis

The resulting model is evaluated on the evaluation set, previously unseen during training. Various procedures for error analysis will be employed. Performance on evaluation data belonging to the same modeled well gives an insight on how the technique can predict un-cored intervals in a well. Evaluation data for another well shows how accurate across-well predictions would be.

In addition to predicting rock properties in un-cored intervals and wells, the resulting abductive network models provide useful information on the modeled relationships. They automatically select input parameters that contribute most to the modeled output and will provide an analytical model relationship that reveals significant input variables and their relative importance and can be easily imported to other analysis/visualization software packages. With neural networks, this information can only be derived through the inspection of large weight matrices.

4.5. Documentation

Full documentation on data sets and pre-processing, model synthesis, resulting model structures, input-output relationships, evaluation analysis, etc. will be prepared.

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