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# Determining In-Situ Stress Profiles From Logs

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## ABSTRACT

This paper presents a new and novel technique for determining the in-situ stress profile of hydrocarbon reservoirs from geophysical well logs using a combination of fuzzy logic and neural networks. It is well established, that in-situ stress cannot be generated from well logs alone. This is because two sets of formations may have very similar geologic signatures but possess different in-situ stress profiles because of varying degrees of tectonic activities in each region. By using two new parameters as surrogates for tectonic activities, fuzzy logic to interpret the logs and rank parameter influence, and neural networks as a mapping tool, it has become possible to accurately generate in-situ stress profiles from logs. This paper demonstrates the improved performance of this new approach over conventional approaches used in the industry.

## INTRODUCTION

In-situ stress plays an important role in all aspects of implementing a hydraulic fracture in oil and gas producing wells. Hydraulic fracture simulators require that the design engineer provide the in-situ stress profile of the well as an input to the simulator. The in-situ stress profile of a well includes the stress at the horizon where the hydraulic fracture is being placed as well as formations immediately above and below of the horizon of interest. The stress contrast between different formations plays an important role in the predicted and actual geometry of a hydraulic fracture.

The vertical confinement of the hydraulic fracture is greatly influenced by the in-situ stress contrast between the “pay” interval and the “barrier” rock. As the value of in-situ stress contrast increase, the fracture height will tend to be more confined and a longer fracture will be created [1]. This is demonsrated for a simple lithology in Figure 1.

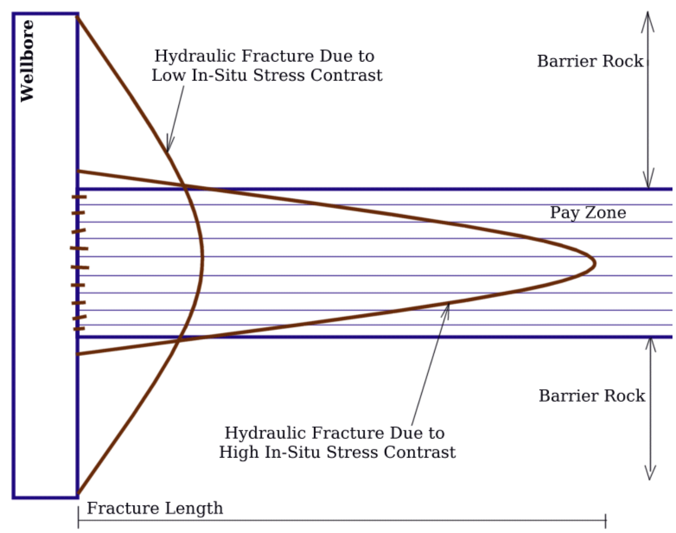


**Figure 1.** Effect of in-situ stress contrast on fracture geometry.

It has been reported that lack of accurate in-situ stress values during the design of a hydraulic fracture can result in as much as 50% error in the actual fracture length upon implementation [1]. This can be quite detrimental in the overall performance of wells that depend on hydraulic fracture design and implementation in order to produce at economic rates. It also would have serious consequences for field development and well spacing.

This paper introduces a new and novel method for determining in-situ stress profiles. The new approach uses well logs as well as other parameters borrowed from the structural engineering community in order to distinguish between regions of different tectonic activities. This approach takes advantage of the unique characteristic of neural networks that can work with non-specific (indirect) information. Furthermore, when using neural network, there is no need to fully understand the inter-relationships between all the parameters.

Currently there are two methods to determine in-situ stress profiles in a formation. First is the physical measurement that is prohibitively expensive, and the second method is to perform deterministic modeling from the well logs that lacks accuracy. These inaccuracies in determining the in-situ stress profile is one of the major contributors to the lack of understanding and accurate modeling of hydraulic fracturing processes.

Previous art has demonstrated that the inaccuracy of the deterministic models, including statistical correlations, is due to lack of incorporation of the tectonic stress component in these models. Furthermore, they make a strong point that tectonic stress cannot be measured at reasonable cost, and even if measured, its relationship with other parameters in the model is not very well understood. The common view in the geophysics community is that unless the tectonic stress issue is correctly addressed, in-situ stress profiling from logs cannot and will not be achieved.

In this paper the authors will compare the existing models as well as the one developed in this study with actual measured in-situ stress profiles from several wells. The applicability of each of these models is tested on all wells. It will be demonstrated that the new approach provides a much improved method for determining in-situ stress profiles using well log data along with, other readily available data that represents an indirect measurement of tectonic stress.

## FUZZY LITHOLOGY EXPERT

One of the best-known methods to calculate in-situ stress from logs is called the ABC method [2]. The ABC method involves the use of defined coefficients for different types of lithology. Prior knowledge of the formation lithology is needed in order to assign the corresponding coefficient. Usually a geologist, a geophysicist or an engineer performs this type of analysis manually. In this study, it was identified that such qualitative information that usually reflects an expert's knowledge can contribute to the determination of the in-situ stress. The best-known analytical technique for incorporation of expert knowledge into calculations is fuzzy logic. Since the knowledge is essentially qualitative in nature it is impractical to use crisp logic (two valued, yes-no logic) to effectively describe and then use it in computations.

Therefore, we developed a three-input, one-output fuzzy expert system to determine the formation lithology from well logs. Details of developing such expert system had been reviewed in a recent JPT article [3]. The inputs to this expert system are Spontaneous Potential, Gamma Ray, and Deep Induction logs while the system output is the formation lithology. Please note that due to the nature of such systems formations are classified such that analyzing two distinct formations, say sandstone and shale, the entire transition zone, where the formation becomes more shaley and less sandy with depth is honored and no information content is compromised.

In order to build a fuzzy expert system that provides accurate lithology from logs, three fuzzy sets of low medium and high was defined for each input log. Then fuzzy rules were defined based on the fuzzy sets. Having three logs and dividing each of the logs into three fuzzy sets of low, medium and high requires 27 fuzzy rules. The fuzzy lithology rule set is presented in Figure 2.

| Spontaneous Potential: Low | Deep Induction: High | Deep Induction: Med. | Deep Induction: Low |
|---|---|---|---|
| Gamma Ray: High | Shale VT | Shale VT | Shale VT |
| Gamma Ray: Med. | Sh/Ss T | Sh/Ss T | Sh/Ss T |
| Gamma Ray: Low | Sh/Carb NNT | Sh/Carb NNT | Sh/Carb NNT |

| Spontaneous Potential: Med. | Deep Induction: High | Deep Induction: Med. | Deep Induction: Low |
|---|---|---|---|
| Gamma Ray: High | Shale T | Shale VT | Shale VT |
| Gamma Ray: Med. | Sh/Carb T | Sh/Ss T | Sh/Ss VT |
| Gamma Ray: Low | Carbonate VT | Sandstone T | Sandstone T |

| Spontaneous Potential: High | Deep Induction: High | Deep Induction: Med. | Deep Induction: Low |
|---|---|---|---|
| Gamma Ray: High | Shale NNT | Shale NNT | Shale NNT |
| Gamma Ray: Med. | Sh/Ss T | Sh/Ss T | Sh/Ss T |
| Gamma Ray: Low | Carbonate VT | Sandstone T | Sandstone VT |

**Figure 2.** Fuzzy rules for lithology identification, VT=Very True, T=True, NNT-Not Necessarily True.

This figure shows that values of spontaneous potential, gamma ray, and deep induction logs are used to determine the lithology of the formation as sandstone, shale and carbonate. Each of the rules is qualified using approximate reasoning methodology as being true, very true, fairly true and not necessarily true. The six rules that are identified as being not necessarily true may be removed from the rule base since it is very unlikely that those values coincide with one another.

Using a fuzzy set theory-based approach for defining formation lithology provides the necessary means to identify rock types that cannot distinctly be defined as sandstone, shale or carbonate. Fuzzy terms that have been used for years in the oil industry such as shaley-sand or sandy-shale are easily accommodated in this approach and contribute to success of the approach presented in this paper.

## ROLE OF TECTONIC ACTIVITIES

A careful survey of the available literature indicates that all investigators that have studied this issue converge upon one common conclusion. The common conclusion is that all the existing approaches (empirical as well as deterministic) fail to incorporate one of the most important factors in determining the in-situ stress in hydrocarbon reservoirs. This factor has been identified as the tectonic stress. The belief is that failing to incorporate tectonic stress into in-situ stress models is the main reason for the inability to match the measured in-situ stress using all the available models. It has further been identified that there are two major problems with incorporating tectonic stress in these models.

First, there is no cost effective way to measure tectonic stress. Second, even if there was, the functional relationship between tectonic stress with the rest of the parameters is yet to be identified. Neural networks provide the solution to address both these issues. First, in order to incorporate the tectonic stress into a neural network we do not ***have to*** have the exact value. It is possible that an indication of tectonic stress would be sufficient. Second, once we identify a surrogate parameter for the tectonic stress the neural network that is by definition a universal function estimator may have the capability to identify and model such relationship based on the available data. Our research for surrogate parameters that could be a substitute for tectonic stress led us to the field of Structural Engineering where ground motion becomes an important factor in building stable structures. We looked for parameters to provide information and distinction between tectonic activities in different parts of the United State. Our research led us to the “Seismic Zone Factor, Z”, and “Spectral Response Acceleration”.

Spectral Response Acceleration is defined as the maximum acceleration that is experienced by a single-degree-of-freedom vibratory system. The spectral response acceleration is used in a number of seismic design procedures, one example is the "NEHRP (national earthquake hazardous program) recommended provisions for seismic regulations for new buildings and other structures." It is defined as the 5 percent damped spectral response acceleration at short periods (0.2 second).

The Seismic zone factor accounts for the amount of seismic risk present in the structure’s seismic zone. There are six zones, with zone 0 representing the least risk. The value of zone factor are intended to represent the effective (not maximum) peak ground accelerations that have only a 10% chance of being exceeded in 50 years.

These two new parameters were introduced to the classic parameters used in the stress calculations. These two parameters deal with geographic position of the wells and are related to the known tectonic activities of the location. The first parameter, the “Seismic Zone Factor, Z” is extracted from “Uniform Building Code for Unites States of America”. The second parameter, “Spectral Response Acceleration” – Earthquake Ground Motion for the Conterminous United States, is obtained from United States Geographical Survey.

Fuzzy logic [4] was used to examine the influence of these new parameters, along with more conventional parameters; in determining the in-situ stress profile. Results are shown in Table 1.

| Rank | Parameter |
|---|---|
| 1 | Depth |
| 2 | Seismic Zone Value |
| 3 | Coefficient "A" |
| 4 | Spectral Acceleration |
| 5 | Spontaneous Potential Log |
| 6 | Pore Pressure |
| 7 | Bulk Density Log |
| 8 | Sonic Log |
| 9 | Gamma Ray Log |
| 10 | Resistivity Log |

**Table 1.** Influence of different parameters on in-situ stress.

This table confirms the prior art that indicated the importance of tectonic activities in a region in calculating the in-situ stress. The two new parameters that were identified as surrogate for tectonic activities are ranked number two and four among the ten studied parameters.

## EXISTING MODELS

In order to show the accuracy of the approach developed in this study, we compared it with existing models developed in the past two decades. Examples of these models can be found in references [5] and [6].

Four existing models were studied. Each of these models are developed based on specific wells. The wells that these methods are based on are Gas Research Institute’s Staged Field Experiment (SFE) #1, SFE #2, SFE #3, and SFE #4. In a typical study engineers will use the available models and apply them to the well they are working with. Most probably the logs are the only information available. Figure 3 shows the measured stress values from well SFE#2 and the calculated stress values by the SFE#2 model. The model seems to do a reasonable job in matching the measured stress values. But this would be expected since the model was developed using these measured stress values. In the same figure, the performance of the other three models (SFE #1, SFE #3, and SFE #4) are shown when trying to predict the measured stress in well SFE #2. As you can see the performance of the models that are based on measurements from other wells degrades significantly.

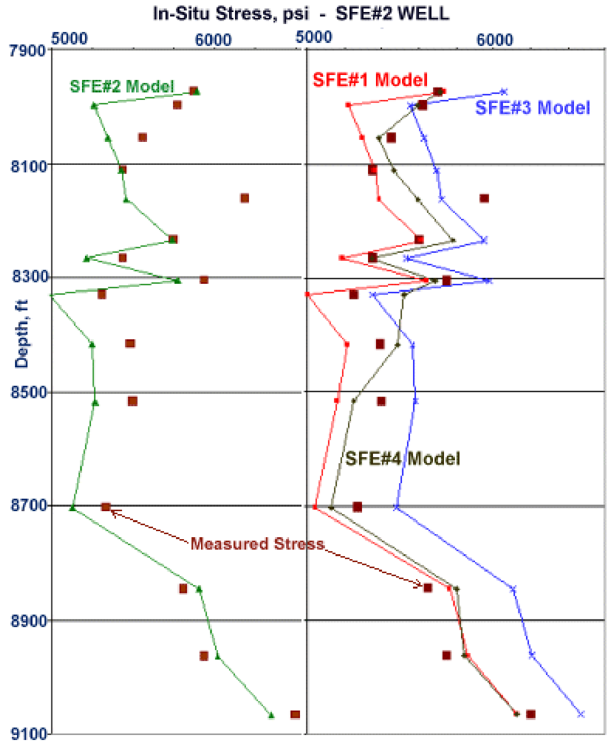


**Figure 3.** Testing applicability of SFE Models to the measured in-situ stress tests from well SFE #2.

Please note that in this figure, starting from the top, the first measurement has been nicely captured by SFE #2, SFE #1, and SFE #4 models while totally missed by the SFE #3 model. The second measurement is captured by SFE #3 and SFE #4 models while missed by the other two. SFE #4 is the only model that captures the third measurement while all models miss the fifth measurement. This behavior is typical of conventional empirical correlations. They cannot capture any information beyond the points that were used during their development, and even then, they do not capture all that is presented.

Figures 4 and 5 show the performance of all models on four separate wells. These wells are AT Mast and Ashland SFOT in Figure 4 and Hogsback and Anderson Canyon in Figure 5. These figures clearly demonstrate the problem with developing deterministic models using data from a particular well and trying to apply it to wells from different locations. In all the cases (except two – SFE #1 and SFE #2 models applied to Ashland SFOT well – Figure 4) the models miss the measured in-situ stress by as little as few hundreds and as much as a thousand psi. Such discrepancy in stress can result in major stimulation design and treatment execution problems. As was mentioned before, it is believed that lack of accuracy during the development of in-situ stress profiles from well logs that is so common with deterministic models has its roots in absence of information regarding tectonic stress in these models. Figures 3-5 are good evidenec of such claims that have appeared in numerous publications. In the next section we demonstrate that intelligent systems let us overcome such short comings.

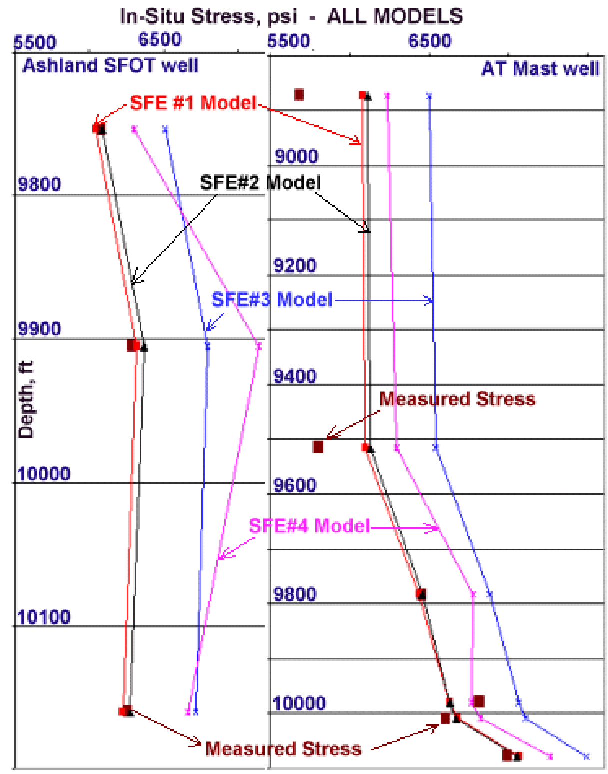


**Figure 4.** Testing all four SFE models' capability in predicting in-situ stress measurements from two wells, AT Mast and Ashland SFOT.

In Figure 5, it is shown that performance of the models for Hogsback well is very poor. Models SFE #1 and #2 are outside of the range that is presented in the graph while SFE #3 and #4, although in the range of the graph are off significantly. Results for the Anderson Canyon well are not too different from that of Hogsback.

## NEURAL NETWOK APPLICATION

In this section we present a new methodology to determine the in-situ stress profile in wells from well logs. This new methodology uses fuzzy logic and neural networks. Fuzzy logic is used to identify formation lithology as demonstrated in previous section and in Figure 2. The result of fuzzy lithology determination is then used as input to the neural network in the form of a coefficient as shown in Table 1.

A backpropagation neural network was used to build the model presented in this study. It must be noted that in order to test the robustness of this methodology several neural models using different architectures and slightly different input parameters were constructed. It was observed this approach is quite robust and allows engineers to predict the measured stresses in a well at different depth with good accuracy. Any new technology that attempts to predict in-situ stress should be measured against the performance of existing models that are presented in the literature. Results of these models on some wells are shown in Figures 3, 4, and 5. Therefore a successful new model must do better than those shown in these figures.

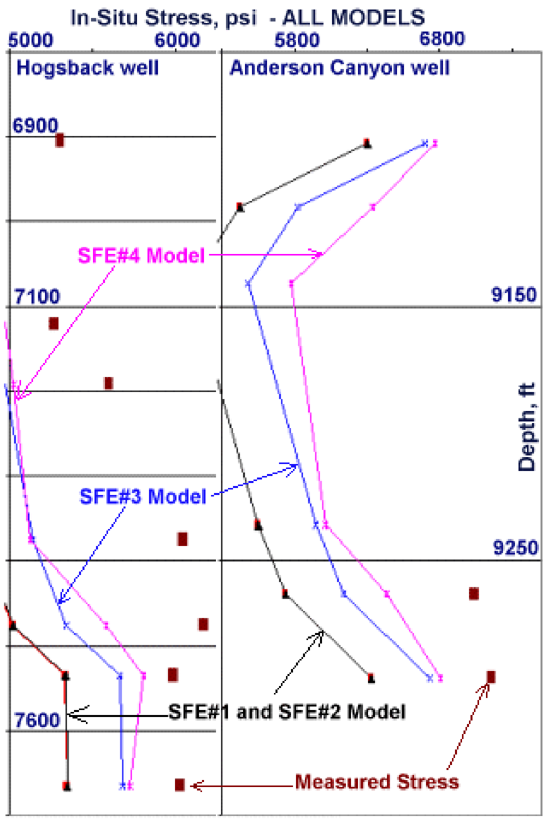


**Figure 5.** Testing all four SFE models' capability in predicting in-situ stress measurements from two wells, Hogsback and Anderson Canyon.

Success of these technologies will be measured by how much better they will predict in-situ stress in wells that were not used during their development. In this study a neural network was develop to predict in-situ stress profile using well logs, and formation lithology as input. Data from five wells namely, Hogsback, SFE#4, SFE2U, AT Mast, and SFE#2L, were used during this development.

The goal of the study was to demonstrate that the process developed here is repeatable and robust. Therefore, each time data from four of the five available wells were used to train and test a neural network and the fifth well was used as the blind well or the verification well. The inputs to the neural network are shown in Figure 2.

Figure 6 show the result of one of the networks were SFE#2L was used as the verification well.

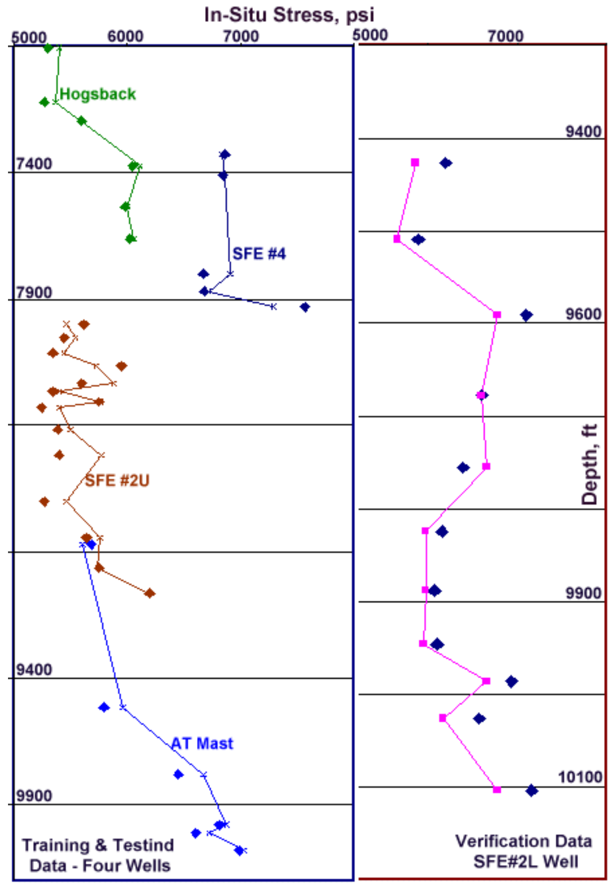


**Figure 6.** Neural network was trained and tested using the measured in-situ stress values in the four wells on the left. The well on the right is used as the verification (blind) well to check network integrity.

It is clear that this result is better than those shown in Figures 3, 4 and 5. In order to test the repeatability of this technique the above process was repeated five times. Each time one of the wells was chosen as the verification well and the remaining four wells were used as the training and testing wells. Each time that this exercise was repeated the results were comparable to those shown in Figure 6.

Figure 7 shows the result of one of these exercises. In this figure, the Hogsback well was selected as the verification well. The result shows the repeatability of using neural networks in order to predict the in-situ stress profile in hydrocarbon reservoirs from well logs and surrogate information that indicates tectonic activities.

It must be mentioned that once the two parameters that are the indicators of the tectonic activities in each region, namely Seismic Zone Factor and Spectral Response Acceleration, are removed from the data set the networks did not perform as well as shown in Figures 6 and 7. This was especially true when in-situ stress measurements from similar formations at similar depths were involved. This further confirmed the conclusions from previous investigators regarding the importance of tectonic activities in the region when measuring in-situ stress.

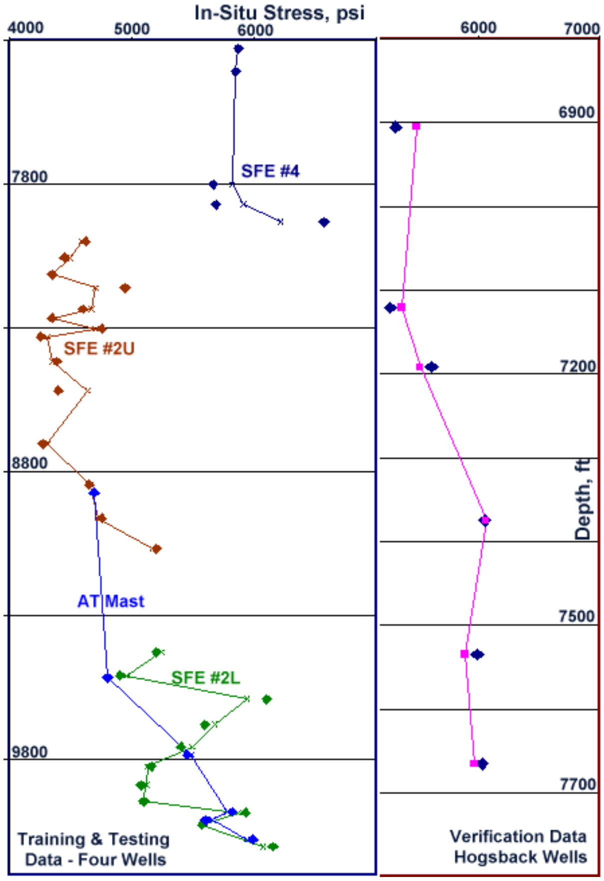


**Figure 7.** Neural network was trained and tested using the measured in-situ stress values in the four wells on the left. The well on the right is used as the verification (blind) well to check network integrity.

## CONCLUSIONS

A new method was presented that incorporates neural networks to predict in-situ stress profiles in the hydrocarbon reservoirs. The stumbling block for predictive modeling had been identified to be different levels of tectonic activities in different regions of country that can significantly contribute to the measurement of different in-situ stress in similar formations. Two new parameters, Seismic Zone Factor and Spectral Response Acceleration were identified in this study to play the role of surrogate indicators of regional tectonic stress.

These parameters were used in conjunction with well log data in a backpropagation neural network for predicting in-situ stress profiles. The comparative study showed that the results obtainable by the neural network were superior to the existing models used in the oil and gas industry.

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