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Permeability Estimation Using a Hybrid Genetic Programming and Fuzzy/Neural Inference Approach

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Abstract

We have developed a methodology that provides permeability estimates for all rock-types or lithologies, for a wide range of permeability. This is a hybrid Genetic Programming and Fuzzy/Neural Net inference system and which utilizes lithologic and permeability facies as indicators. This work was motivated by a need to have a volumetric estimate of permeability for reservoir modeling purposes. To this end, for our purposes,the inputs to this process are limited to properties that can be estimated from seismic data. The permeability transform is first estimated at the well locations using core permeability, elastic parameter logs and porosity. The output from the process can then be used, in conjunction with estimates of these properties from 3D seismic data, to provide an estimate of permeability on a volume basis. The inputs are then, the volume of shale (Vsh) or any other log type used to determine lithology, the sonic and density logs, the porosity log and core permeability measurments. The transform system is composed of three distinct modules. The first module serves to classify lithology and separates the reservoir interval into user-defined lithology types. The second module, based on Genetic Programming, is designed to predict permeability facies within lithology type. A permeability facies is defined as as a low, medium or high permeability set associated with each lithology type. A Fuzzy/Neural Net inference algorithm makes up the third module of the system, in which a TSK fuzzy logic relationship is formed, for each permeability facies and lithology.

The system has been applied in two oil fields, both offshore West Africa. In comparison with current estimation approaches, this system yields more consistent estimated permeability. The results from conducting cross-validation suggest this methodology is robust in estimating permeability in complex heterogeneous reservoirs. This system is designed to use elastic log properties inverted from seismic data, such as acoustic velocity and density as input so permeability volume can be obtained.

Introduction

Knowledge of the spatial variability of permeability is of great importance in reservoir modeling. However, core permeability measurments are very limited and tend to be biased. While it is commonly observed that permeability has some correlation with wire-line data, there is no theoretical equation to describe such a relationship. In general, developing a generic system that produces good permeability estimates for all types of lithologies is a difficult task. Permeability estimation continues to pose a significant challenge to reservoir characterization and simulation.

In the past few years, tremendous effort has been expended in the generation of a large variety of approaches to estimating permeability utilizing wire-line logs: multi linear regression, principal components analysis and clustering, non-linear Neural Network, and fuzzy logic among them. All those methods involve using some form of indicator, such as lithology type, electro-facies (Mathisen, et al, 2001, Lee, et al, 2002), grain-size, litho-facies (Suryanarayana, et al, 2003), or hydraulic flow unit (Badarinadh, et al, 2002, Fahad, et al, 2000) to improve the permeability estimation. Introducing such indicators allows one to establish different relationships which can then be applied to the associated intervals or units of interest.

In complex heterogeneous reservoirs, however, these methods happen to miss-estimate the high permeability layers or produce low resolution permeability “logs”. In addition, some of those indicators, such as grain-size indicator, are not easy to obtain and are certainly not available on a reservoir wide scale. The permeability of reservoir sequences in these types of depositional environments exhibits significant changes even within the same “lithologic indicator” or “electro-facies indicator”. It is not unusual that the permeability related to reservoir lithologys range from 10 md to 1000 md. To attempt to account for this wide variation we decided to use permeability facies (high, low, medium) as an indicator. Moreover, the permeability facies could have different meaning for different lithology types. For instance, the high permeability facies of sandstone might indicate a permeability range from 500 to 1000 md while for shaly sand the range may be from 50 to 100 md. This indicator scheme or partitioning is a "flag" process, that is, estimated values are categorical, instead of continuous. Categorical values are very difficult to assign using wire-line logs with linear or non-linear regression type techniques. Our studies show that Genetic Programming (GP) provides more stable "flag" or categorical estimation in comparison to multi-linear regression, Neural Network, and decision tree methods (Quinlan, 1993).

Now that we have partitioned the input dataset into sets characterized by permeability facies and lithology type, we wish to estimate permeability for each of these sets independently. In this study, we utilize a combined system of Fuzzy Inference and Neural Network to do the permeability estimation. One advantage of using Fuzzy Inference is that we can account for the imprecision and uncertainty in the input values.

We will briefly discuss the Genetic Programming and Fuzzy Inference algorithms, and then introduce our hybrid permeability estimation process with the applications into two oil fields, both offshore West Africa.

Genetic GP and Fuzzy Inference

GP is a symbolic regression method (Koza, 1992). GP training cycle (**Figuer 1**) starts with a population of randomly generated classifiers. Depending on their fitness, calculated by the percentage of the training data that are correctly classified, two classifers with higher fitness in the tournament selection become the winner for reproduction. If two candidates are "tied" in their hit rate, the mean squared error measurement is used to select the winner. Reproduction is done by a combination of crossover and mutation. The two generated offsprings replace the worst classifiers in the population. This select-reproduce-replace cycle continue for many generations until the termination criterion is met (Yu, et al., 2003).

Adaptive Neural-Fuzzy Inference System (ANFIS) is a fuzzy modeling tool that generates Takagi-Segeno-Kang (TSK) type fuzzy inference system which is based on the given input and output data. A TSK fuzzy system has the following structure (Jang, 1993).

The first component is a set of input membership functions (MFs). Membership functions map crisp data to linguistic values or labels. Fuzzy Inference system uses conditional statement in if-then format. The if-part consists of linguistic values and fuzzy operators (AND, OR, and NOT). The then-part is a first order linear equation. Based on the conditions or fuzzy rules, the inference system interprets input values and assigns output values. In TSK system, the output values are calculated based the weight of each rule, as shown in **Figure 2**. The construction of ANFIS is automatic through a two step learning process: (1) the network structure is built by a subtractive clustering algorithm; and (2) the input membership function parameters are tuned by a back propagation algorithm while the output parameters are tuned by a least square estimation.

Hybrid GP and Fuzzy/Neural Permeability Estimation System

Our hybrid system consists of three modules. The first module serves to classify lithology and separates reservoir interval into user-defined lithology types. The second module (GP based) is designed to determine permeability facies within each lithology type. Permeability facies are defined as low, medium or high permeability zones associated with lithologies. A Fuzzy/Neural Net inference algorithm makes up the third module of the system in which a TSK fuzzy logic relationship is derived for each permeability range. Given the input data, the system analyzes the lithology types, classifies the permeability facies, and then estimates the permeability values (**Figure 3**).

For the permeability facies estimation we decided to have high, medium, and low permeability facies related to each lithology type. In some cases, however, two facies are enough. The number of facies may also be dependent on the number and distribution of core permeability samples. The GP module captures the errors and restarts the process if the GP misclassification reaches unacceptable levels. This second module is of vital importance of the overall system performance as generates the permeability facies (categorical values) which will be pipelined to the Fuzzy/Neural permeability estimation process.

The Fuzzy/Neural module estimates the actual permeability values. The process is very similar to non-linear regression methods. The main difference is that its internal engine utilizes fuzzy rules. Each input well log has its own rules in the form of membership functions and weight factors trained with the input logs and core permeability. The estimated permeability is the result of inferring or interpreting those fuzzy rules with core permeability.

Applications

The hybrid GP and Fuzzy/Neural system has been applied in two oil fields, both offshore West Africa, to estimate the permeability of reservoir sequences. In those two deep water fields, the reservoirs are highly heterogeneous and the permeability is highly variable not only among different lithology types and but also within the same lithology type. As a result, the relationships of core permeability to the measured logs are extremely difficult to derive.

In the first field, five wells are available with core permeability. Each of these wells is at least half a mile from its neighbors. Wire-line logs, including sonic and density, have been recorded in each well. **Figure 4** shows the plot of the core permeability against the volume of shale (Vsh) indicating the changes in permeability are significant both among and within the lithology types. It is clear that the variations could lead to considerable uncertainty by using simple regresion to estimate the permeability. The critical decision that needs to be made is how to partition Vsh into different lithology types so that each one has similar geological properties or easily recognizable patterns of permeability distribution. One way to define lithology type is based on the cutoffs of Vsh. It is possible to define these partitions with either a sharp or fuzzy boundary. In this study, we simply apply sharp cutoffs to determine each lithology type. Based on the Vsh distribution and formation evaluation (FE) analysis, five lithology types are defined: sand (Vsh < 15%), shaly sand (Vsh 15-40%), high impedance sand (Vsh < 15% and P-wave velocity > 7200 ft/s), sandy shale (Vsh 40-75%), and shale (Vsh > 75%). The high impedance sand, which has a P-wave velocity greater than 7200 ft/second, only has high permeability.

The input data, beside core permeability, are total porosity, P-wave velocity and bulk density. During the training process, we specify permeability facies as high, medium, and low. Note that the shale has low and medium permeability facies and high impedance sand requires only one facies, i. e., high permeability facies. The cutoffs for the three facies depend on the lithology type and are different as shown in **Table 1**. As expected, the permeability facies for the sand and shale are easy to model for all the five wells. In contrast, the sandy shale has the most complicated relationship to the core permeability. As a result, its classifiers have the lowest accuracy rate. The detailed accuracy of the GP is given in **Table 2**.

The system generates permeability estimations that are well correlated with the core permeability for all lithology types. The correlation coefficient values (R^2) are between 0.9 and 0.95. We combined the GP classifiers with the TSK system and then ran the overall system on the input data. **Figure 5** shows the results. Among the five lithology types, the sandy shale has the worst match between the estimated and the core permeability. This is due to the misclassification of permeability facies by the GP classifiers.

Our comparison study shows that the hybrid GP-fuzzy system outperforms the current system on all the data from the five wells (**Figure 6**). We also made detailed performance comparisons with the previous system using data from one well (well C). **Figure 7** shows that the hybrid system (* Perm-FIS) produces permeability estimations that match the core permeability (Perm-Core) better than the two previous works. Note that Perm-Log is the current systems while Perm-Vsh is the system used Vsh as the only input. For instance, the Core-Perm ("+" in **Figure 7**) between depth 6340 and 6360 feet are with high values (>1000 md). The values decrease between 6335 and 6340 feet and raise again at 6330 feet. The hybrid system yields permeability estimations that match this trend of high-low-high pattern very well. In contrast, Perm-Vsh matches badly to the Core-Perm trend. Another previous work, Perm-Log gives a better match than Perm-Vsh does. However, its estimations match poorly between the depth of 6325 and 6340 feet where Core-Perm drops.

For a totally blind test, this system is applied to the second field where one well is used. In this field, the overall core permeability is much lower than that from the previous field. Four lithology types: sand, shaly sand, sandy shale, and shale, are determined. There is no high impedance sand. The cutoffs for permeability facies are listed in **Table 3**. The input logs, again, are total porosity, sonic and bulk density. The input data set is equally divided into three sub-datasets which are used for training, validation, and testing. The results show a very good match to the core permeability (**Figure 8**).

Conclusions

A hybrid GP-Fuzzy/Neural system has been shown to be robust in estimating permeability from elastic parameter input. The divide-and-conquer approach is very effective in dealing with highly heterogeneous reservoirs. This is demonstrated in the exceptional performance of the hybrid system. Once the lithology type and permeability facies are identified, the estimation of permeability becomes more robust and easier. In comparison with current estimation approaches, this system yields the estimated permeability that matches core permeability more consistently. This system is capable of using input data which is derivable from seismic as input and creating an output permeability volume.

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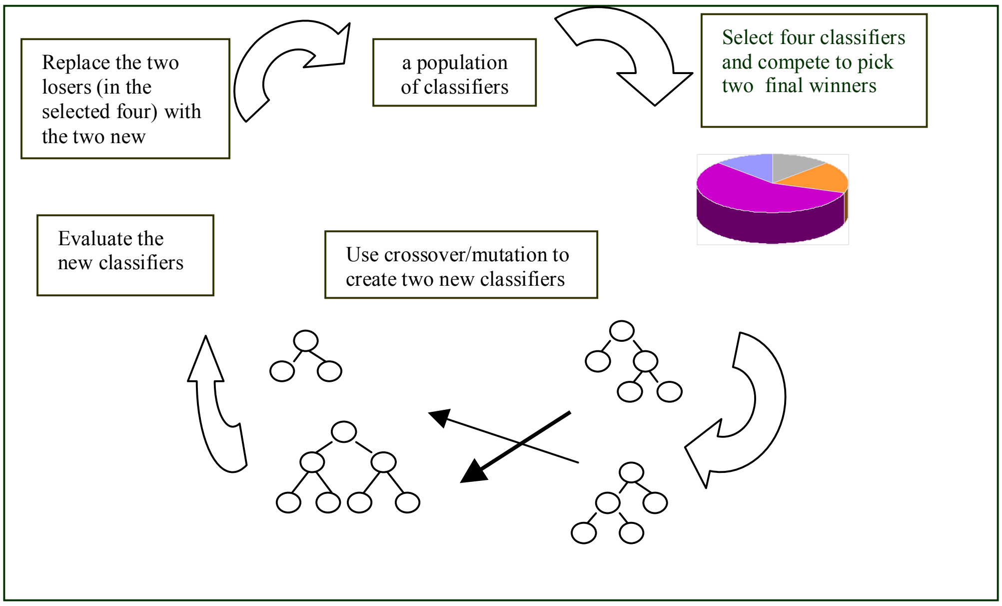

Figure 1 Genetic Programming cycle

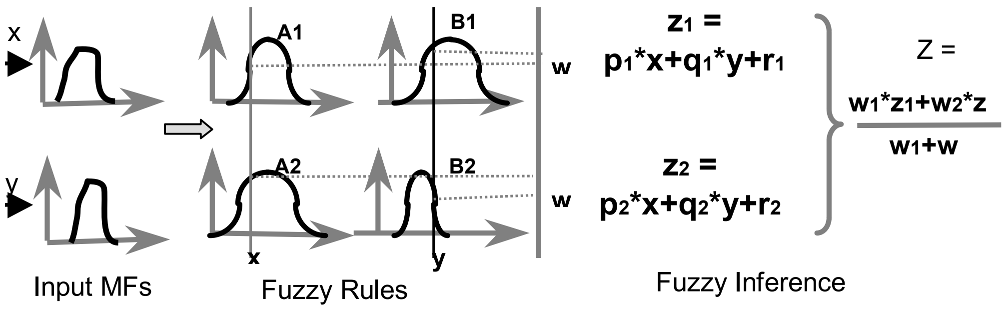

Figure 2 TSK fuzzy inference system structure

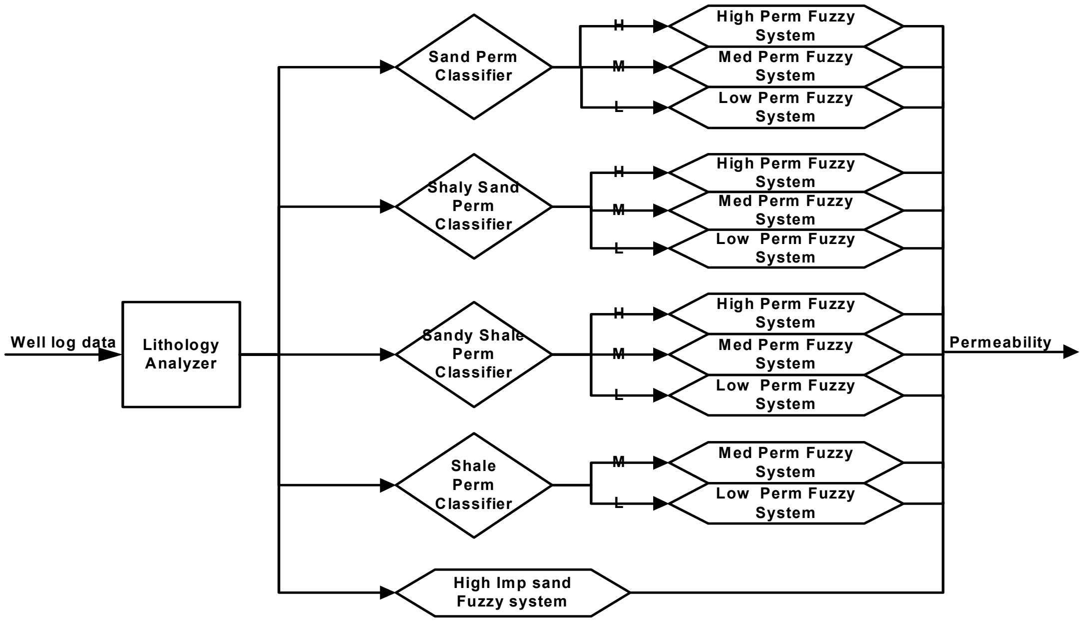

Figure 3 GP and fuzzy hybrid system high-level tructure

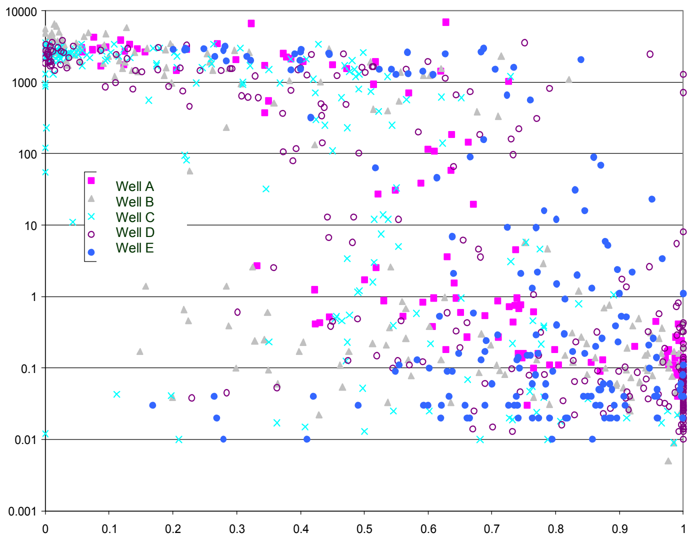

Figure 4 Core permeability vs. Vsh (five wells)

Lithology type	High permeability	Medium permeability	Low permeability
Sand	>1000 md	1000-100 md	<10 md
High imped. sand	>1000 md		
Shale sand	>300 md	300-100 md	<10 md
Sandy shale	>300 md	300-100 md	<10 md
Shale sand		>10md	<10 md

Table 1 Permeability facies cutoffs for different lithology

	sand	shaly sand	sand shale	shale
High permeability	93.2%	93.8%	67.5%	
Medium perm.	82.9%	79.0%	79.0%	85.0%
Low permeability	100.0%	88.9%	80.6%	96.6%

Table 2 Classification accuracy of GP classifier

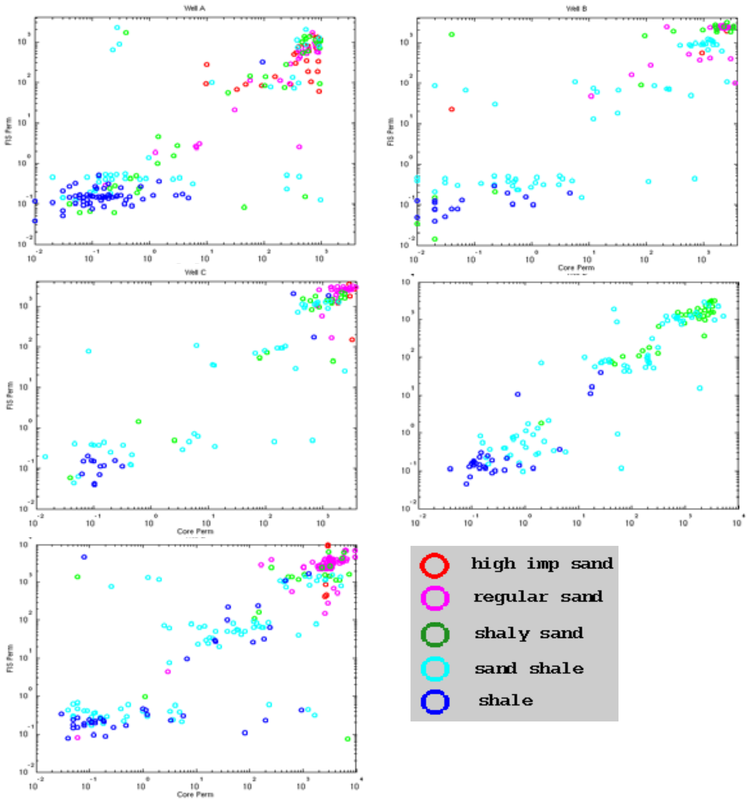

Figure 5 Core vs. estimated permeability from hybrid system

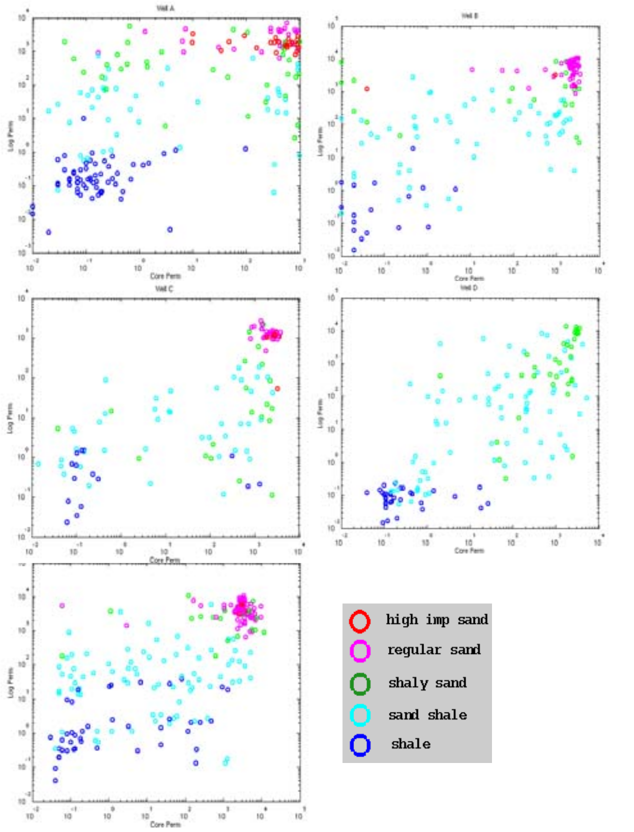

Figure 6 Core vs. estimated permeability using existing method

	High permeability	Medium permeability	Low permeability
Sand	>100 md	100-20md	<20md
Shaly sand	>100 md	100-1 md	<1md
Sandy shale	>100 md	100-1 md	<1md
Shale	>10md		<10 md

Table 3 Permeability facies cutoffs for different lithology types of the second field

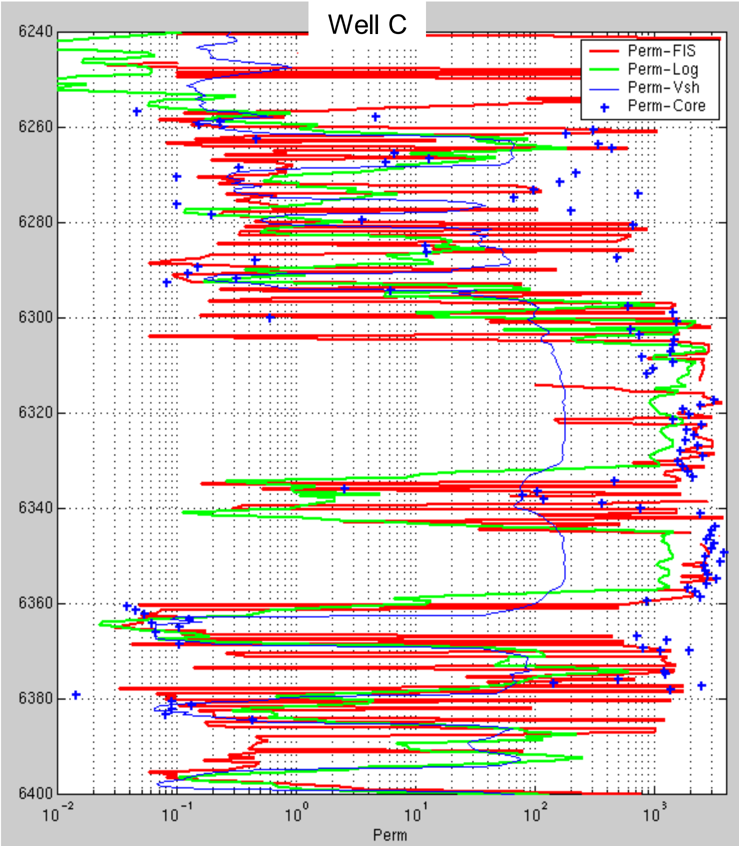

Figure 7 Performance comparisons of hybrid system with two previous systems

Perm-FIS: Our GP and Fuzzy/Nerual hybrid
Perm-Log: Multi-regression using five logs
Perm-Vsh: Regression using Vsh only
Perm-Core: Core permeability samples

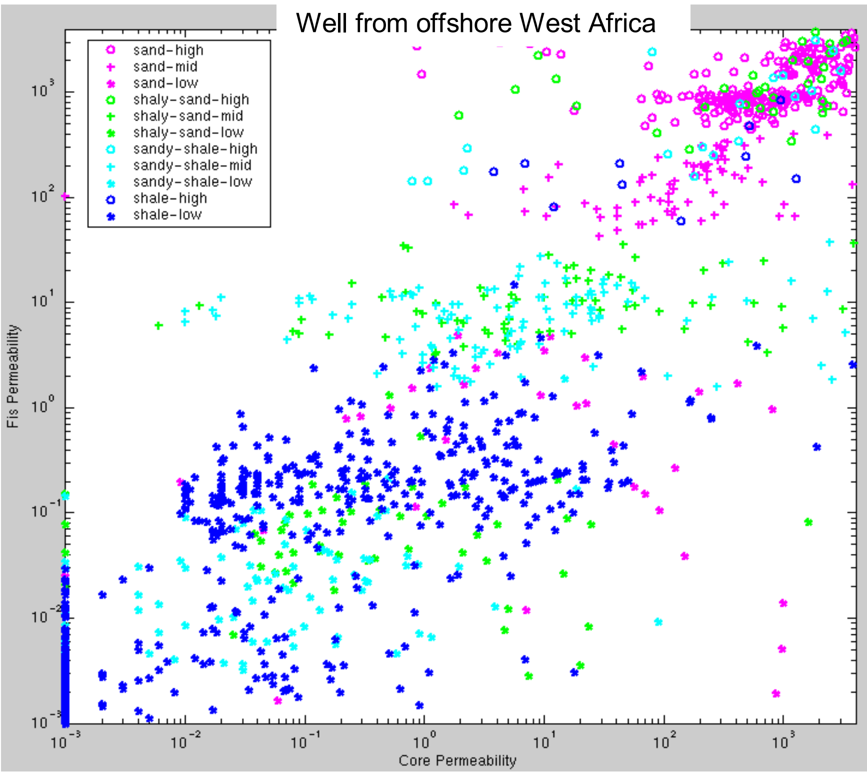

Figure 8 The blind test results of hybrid system of the second field (one well only, core vs. estimation)