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Reservoir Characterization Through Synthetic Logs

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Abstract

Magnetic resonance logs provide the capability of in-situ measurement of reservoir characteristics such as effective porosity, fluid saturation, and rock permeability. This study presents a new and novel methodology to generate synthetic magnetic resonance logs using readily available conventional wireline logs such as spontaneous potential, gamma ray, density, and induction logs. The study also examines and provides alternatives for situations in which all required conventional logs are unavailable for a particular well. Synthetic magnetic resonance logs for wells with an incomplete suite of conventional logs are generated and compared with actual magnetic resonance logs for the same well.

In order to demonstrate the feasibility of the concept being introduced here, the methodology is applied to a highly heterogeneous reservoir in East Texas. The process was verified by applying it to a well away from the wells used during the development process. This technique is capable of providing a better image of the reservoir properties (effective porosity, fluid saturation, and permeability) and more realistic reserve estimation at a much lower cost.

Introduction

In a recent SPE paper[1] it was shown that it is possible to generate virtual magnetic resonance logs using conventional wireline logs. The concept was tested on several wells from different locations in the United States and the Gulf of Mexico. It was demonstrated that using virtual intelligence techniques (artificial neural network in this case) it is possible to generate accurate virtual magnetic resonance logs. It was further demonstrated that using the virtual magnetic resonance logs for reserve calculation provides very accurate estimations (within 3%) when compared to reserve estimation obtained by actual magnetic resonance logs.

The major shortcoming of that study was the fact that the development and the testing of the process were performed on the same well. In that study part of the pay zone was used for the model development and then the model was tested on the rest of the pay zone. The main reason for that shortcoming was lack of data. The study was conducted on several fields but from each field data was available from only one well. It was mentioned that the ultimate test for this methodology would be when data from several wells in a particular field would be available, so the methodology can be tested in a manner that would simulate its actual use. This methodology would work best when conventional logs are available from most of the wells in the field and magnetic resonance logs are performed only on a handful of wells (these wells should also have the conventional logs). The wells with magnetic resonance log will be used for model development and consequent testing and verification of the model. Then the developed (and verified) model will be applied to all the wells in the field. This would generate a much better and more realistic picture of the reservoir characteristics for the entire field. Having such an accurate picture of reservoir characteristics would be a valuable asset for reservoir simulation, modeling, and reservoir management.

This paper provides the ideal test bed for this methodology. Here the methodology is applied to a field in East Texas (Cotton Valley formation) that is known for its heterogeneity as well as for the fact that the well logs and reservoir characteristics are non-correlatable from well to well. A recently published paper[2] demonstrated the non-correlatable nature of formation characteristics and well logs in this formation.

Methodology

The study area includes a total of 26 wells. There is magnetic resonance logs available from only six wells. The other 20 wells have conventional logs but no magnetic resonance logs. Figure 1 demonstrates the relative location of the wells. In this figure wells with magnetic resonance logs are shown with circles and are named MR-1, MR-2, etc. Wells that have no magnetic resonance logs are shown with asterisks and are named W-1, W-2, etc. Also no conventional porosity logs are available for wells with magnetic resonance logs. This could simply be due to the fact that magnetic resonance logs provides effective porosity values that are much more accurate than their conventional counterparts such as neutron porosity, density porosity, and bulk density logs, so not running these logs was an economic decision. Table 1 provides a complete list of the wells and logs that were available for each well in this study.

In a previous study[1] it was observed that existence of porosity indicator logs such as neutron porosity, density porosity, and bulk density, is helpful during the model building process. Therefore it was decided to generate the virtual version of these logs for the wells with magnetic resonance logs prior to attempting to develop the virtual magnetic resonance logs. Therefore the process of generating virtual magnetic resonance logs becomes a two-step process. A set of neural networks is trained in order to provide input for another set of neural networks. This may sound counter-intuitive from a neural network theoretical point of view. A strong and theoretically sound argument can be made that since neural networks are model free function estimators, and since they are part of an armament of tools that are capable of deducing implicit information form the available data, then adding a set of input values that are essentially a function of other inputs (since they have been generated using the same inputs) should not provide any additional information.

Actually, the opposite of this approach is usually practiced. In cases that there are many input parameters but not as many training records, several analysis including principal component analysis are used to identify the codependency of input parameters to one another and removing those input parameters that are a function of others inputs.

Authors' respond to such an argument would be as follows. Theoretically there is an ideal neural network structure that when coupled with the ideal training algorithm and ideal neural network parameters will be able to generate the same result with the original inputs and there will be no need for supplemental inputs generated by another set of neural networks, which are the porosity indicator logs such as neutron porosity, density porosity and bulk density in this case. But since such a network is not available, certain (not any) functional relationships (that can be based on domain expertise) between input parameters can indeed help the training and learning process by explicitly revealing some valuable information. A schematic diagram of the two-step process used for the development of virtual magnetic resonance logs are presented in Figure 2.

Synthetic Conventional Logs

As was mentioned in the previous section the process of developing virtual magnetic resonance logs starts by generation of synthetic conventional logs. Therefore the wells that had a complete suite of conventional logs were used to develop a neural network model that is capable of replicating the conventional logs such as neutron porosity, density porosity and bulk density for the wells with magnetic resonance logs that lack these logs.

In order to make sure that the neural network model that we are building provides accurate suite of porosity indicator logs well W-10 was used as a test well. This simply means that the data from this well was not used during the training and model building process; rather it was put aside so the capabilities of the trained neural network or neural model can be tested and verified. Figure 3 shows the actual and virtual versions of all three logs (neutron porosity, density porosity, and bulk density) for the well W-10.

As can be seen in this figure, we have been successful in building a representative model that is capable of generating virtual porosity indicator logs for this field. The virtual (synthetic) logs closely follow the trend of the actual logs. All these porosity indicator logs were generated for the wells with magnetic resonance logs. In order to further demonstrate the validity of the virtual (synthetic) porosity indicator logs, neutron porosity logs of three wells were plotted on the same graph. This is shown in Figure 4. These wells (MR-2, MR-4 and W-10) are in the proximity of each other. MR-2 and MR-4 did not have any conventional porosity indicator logs and well W-10's conventional porosity indicator logs were not used during the model development process. Figure 4 shows the virtual neutron porosity for all three wells as well as the actual neutron porosity for well W-10. Formation signatures are easily detectable from all these wells. The distance between these wells W-10 and each of the wells MR-2 and MR-4 is about 7000ft. These distances are indicated with a line in Figure 1.

The methodology explained in this section can be used in many different situations where a complete suite of logs is required for all wells but cannot be accessed due to the fact that some wells lack some of the logs.

Virtual Magnetic Resonance Logs

Several good papers and reviews about magnetic resonance logs have been published,[3-8] hence this technology will not be discussed in this paper. As was mentioned before the objective of this study is to develop a methodology that significantly decreases the cost of field-wide reservoir characterization by generating virtual magnetic resonance logs for all the wells in the field. This will be done through selecting a few wells in the field to be logged using the magnetic resonance logging tools and using this data to develop an intelligent model that can replicate the magnetic resonance logs for other wells in the field.

If a company decides to use this methodology on one of its fields it would be desirable to start by some planning prior to performing any magnetic resonance logging in the field. This would have an important impact on the modeling process. During the planning process the number of the wells that should be logged using the magnetic resonance tools and the location of these well with respect to the rest of the wells in the field would be among the important consideration. In other cases (such as the one in this study) we have to do with the data that is available and make the best of it.

As seen in Figure 1, there are six wells in this part of the field that have magnetic resonance logs. The goal is to use the magnetic resonance logs from these wells and develop a predictive, intelligent model that can generate virtual (synthetic) magnetic resonance logs from conventional logs such as gamma ray, SP, induction, and density logs for all the wells in the figure. As was mentioned in the prior section, in this field some of the wells did not have porosity indicator logs. Therefore synthetic version of these logs had to be constructed for these wells prior to generation of virtual magnetic resonance logs.

Prior to using all the six wells with magnetic resonance logs to generate virtual magnetic resonance logs, a test and verification process should be performed in order to confirm the validity of the approach for the specific field and formation under investigation. This test and verification process is the main subject of this paper. During this process we demonstrate that the methodology of generating virtual magnetic resonance logs is a valid and useful process. We demonstrate this by using five of the wells, MR-2, MR-3, MR-4, and MR-5, to develop an intelligent, predictive model and generate virtual magnetic resonance logs for well MR-1. Since the magnetic resonance logs for well MR-1 are available, but not used during the model building process, it would provide an excellent verification well. Furthermore, since well MR-1 is on the edge of the section of the field being studied, and is somewhat outside of the interpolation area, relative to wells MR-2 through MR-6, it would stretch the envelope on accurate modeling. This is due to the fact that the verification is done outside of the domain where modeling has been performed. Therefore, one may claim that in a situation such as the one being demonstrated here, the intelligent, predictive model is capable of extrapolation as well as interpolation. Please note that here, extrapolation is mainly an areal extrapolation rather an extrapolation based on the log characteristics.

Figure 5 shows the actual and virtual magnetic resonance logs (MPHI - effective porosity, and MBVI - irreducible water saturation) for well MR – 1. This figure shows that this methodology is quite a promising one. Although one may argue that the virtual logs under-estimate both effective porosity and irreducible water saturation in many cases, the fact that they are capable of detecting the trend and identifying the peaks and valleys of the formation characteristics are very encouraging. It is believed that using virtual porosity indicator logs such as neutron porosity, density porosity and bulk density logs during the training process has contributed to the under-estimation of the magnetic resonance logs. Although it was demonstrated that the virtual porosity indicator logs are quite accurate, it is desirable to train the networks with the best possible data.

Figure 6 shows the actual and virtual magnetic resonance permeability logs - MPERM - for the same well (MR-1). Since MPERM log is not a direct measurement log rather a calculated log (it is a function of effective porosity and irreducible water saturation logs), it is expected that the virtual logs under-estimate the permeability when compared to actual calculated MPERM log. Again, the virtual log is capable of detecting most of the trends in permeability values in this formation. If the virtual log were used as a guide to identify perforation depth intervals in this formation, it would have done its job well.

In order to test and verify the effectiveness of the virtual magnetic resonance logs, as compared to its actual counterparts, they were used in a reserve estimation calculation. In this calculation all parameters were kept constant and the only difference between two sets of calculation were the use of virtual verses actual magnetic resonance logs. The logs shown in figures 5 are used to n in the reserve estimate calculations. Using the virtual magnetic resonance logs the estimated reserves were calculated to be 138,630 MSCF/Acre while using the actual magnetic resonance logs the calculated reserve estimates were 139,324 MSCF/Acre for the 400ft of pay in this well. The 0.5% difference in the calculated estimated reserves based on virtual and actual magnetic resonance logs demonstrates that operators can used this methodology effectively to reach at reserve estimates with much higher accuracy at a fraction of the cost. This will allow operators make better reserve management, and operational decisions.

It should also be noted that authors believe that this methodology can be improved using an integrated hybrid virtual intelligence approach. This integrated-hybrid approach uses fuzzy set theory as well as neural networks to improve the modeling process. Results from this new approach will be published soon.

Conclusions

A new methodology was introduced that has the potential to reduce the cost of reservoir characterization from well logs significantly. This methodology uses the conventional well logs and generates virtual or synthetic magnetic resonance logs for all the wells in a field. The development process requires that only a handful of wells in a field be logged using the magnetic resonance logging tools. Then the data generated from the magnetic resonance logging process is coupled with the conventional log data and used to develop an intelligent, predictive model. After testing and verifying the predictive model's accuracy, it can be applied to all the wells in the field that have only conventional logs. At the end of the process all the wells in the field will have magnetic resonance logs. This process will help engineers in the filed to acquire a much better handle on the reservoir characteristics at a fraction of the cost of running magnetic resonance logs on all the wells in the field. This is especially true and beneficial for fields that have many producing wells the already have been cased.

It was also demonstrated that virtual magnetic resonance logs could provide reserve estimates that are highly accurate when compared to the reserve estimates that can be acquired from actual magnetic resonance logs.

Acknowledgment

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Reference

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Well ID	CALI	SP	GR	ILD	ILM	SFL	NPHI	DPHI	RHOB	MBVI	MPERM	MPHI
MR - 1	X	X	X	X	X					X	X	X
MR - 2	X	X	X	X	X	X				X	X	X
MR - 3	X	X	X	X	X	X				X	X	X
MR - 4	X	X	X	X	X	X				X	X	X
MR - 5	X	X	X	X	X					X	X	X
MR - 6	X	X	X	X	X					X	X	X
W - 1	X	X	X	X	X		X	X	X			
W - 2	X	X	X	X	X	X	X	X	X			
W - 3	X	X	X	X	X	X	X	X	X			
W - 4	X	X	X	X	X	X	X	X	X			
W - 5	X	X	X	X	X	X	X	X				
W - 6	X	X	X	X	X		X	X	X			
W - 7		X	X	X		X	X	X				
W - 8		X	X	X			X	X				
W - 9	X	X	X	X	X		X	X				
W - 10	X	X	X	X	X	X	X	X	X			
W - 11	X	X	X	X		X	X	X	X			
W - 12	X	X	X	X	X	X						
W - 13	X	X	X	X	X	X	X	X	X			
W - 14	X	X	X	X	X	X	X	X				
W - 15	X	X	X	X	X		X	X	X			
W - 16	X	X	X	X	X	X		X				
W - 17	X	X	X	X	X		X	X	X			
W - 18	X	X	X	X	X	X	X	X	X			
W - 19	X	X	X				X	X	X			
W - 20	X	X	X	X	X	X	X	X	X			

Table 1. List of the wells in this study and available logs for each well.

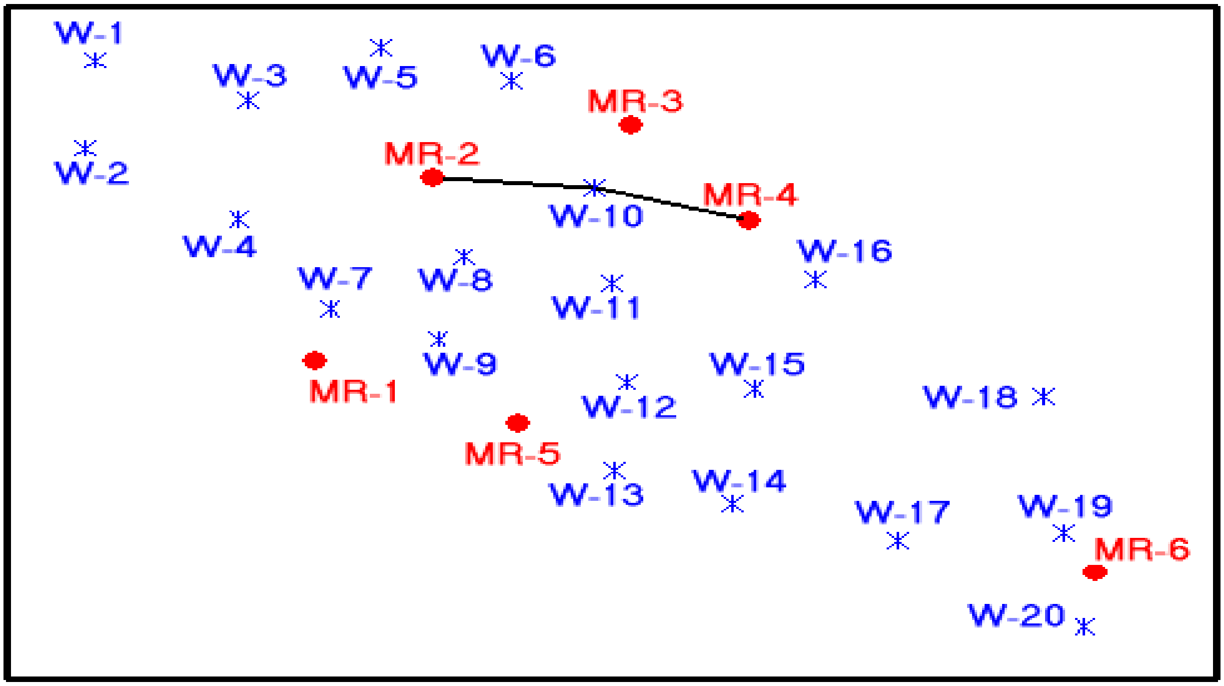

Figure 1. Relative location of wells in the Cotton Valley, East Texas.

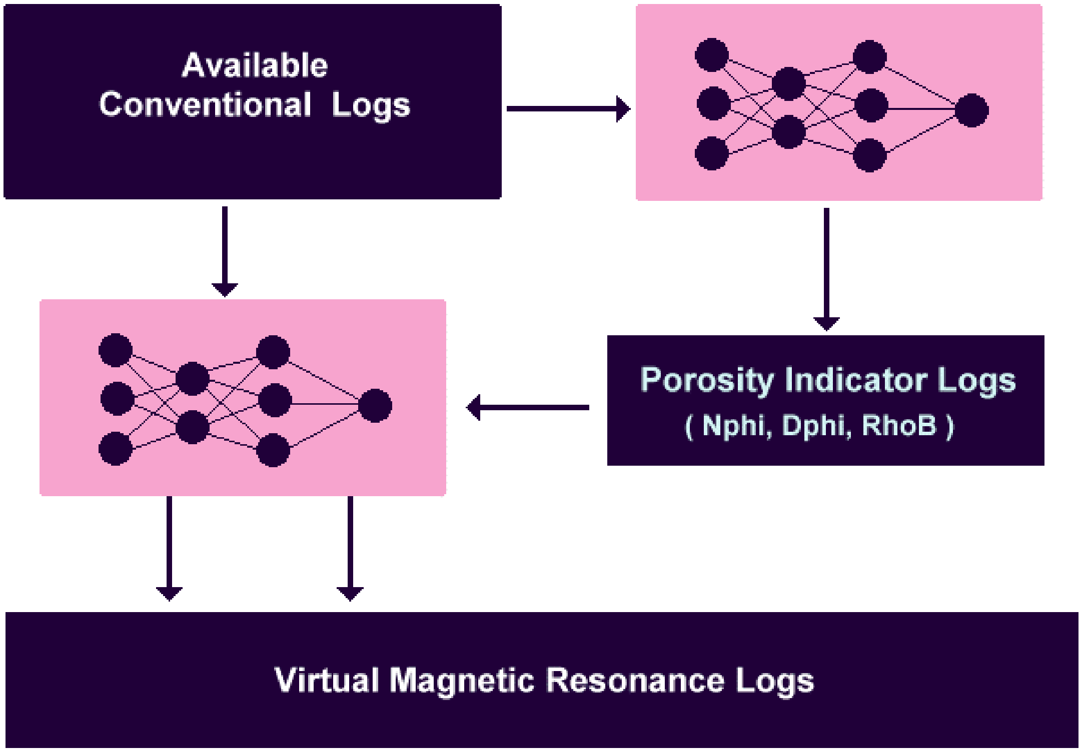

Figure 2. Schematic diagram of the process for developing virtual magnetic resonance logs.

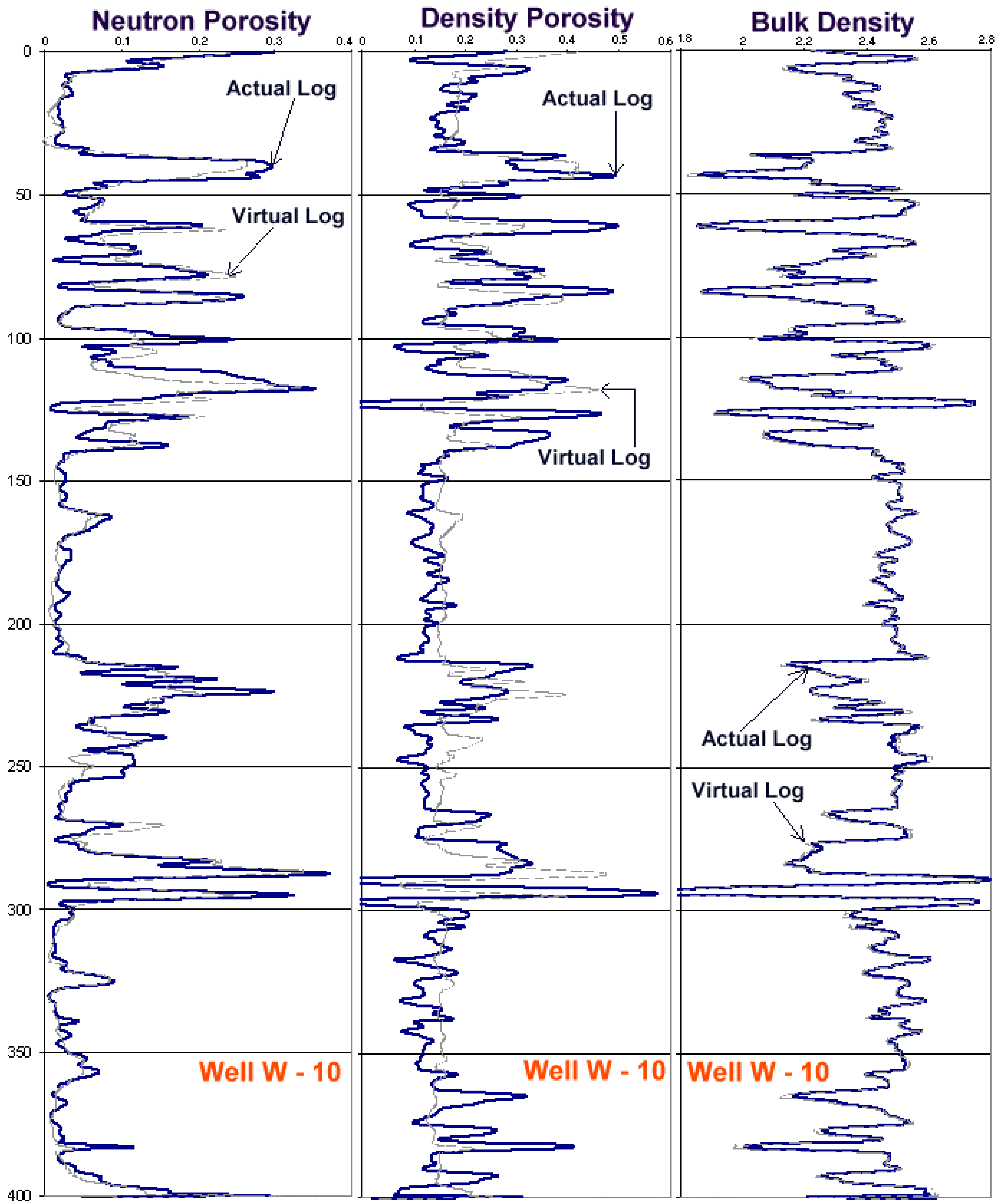

Figure 3. Actual and virtual porosity indicator logs for well W-10.

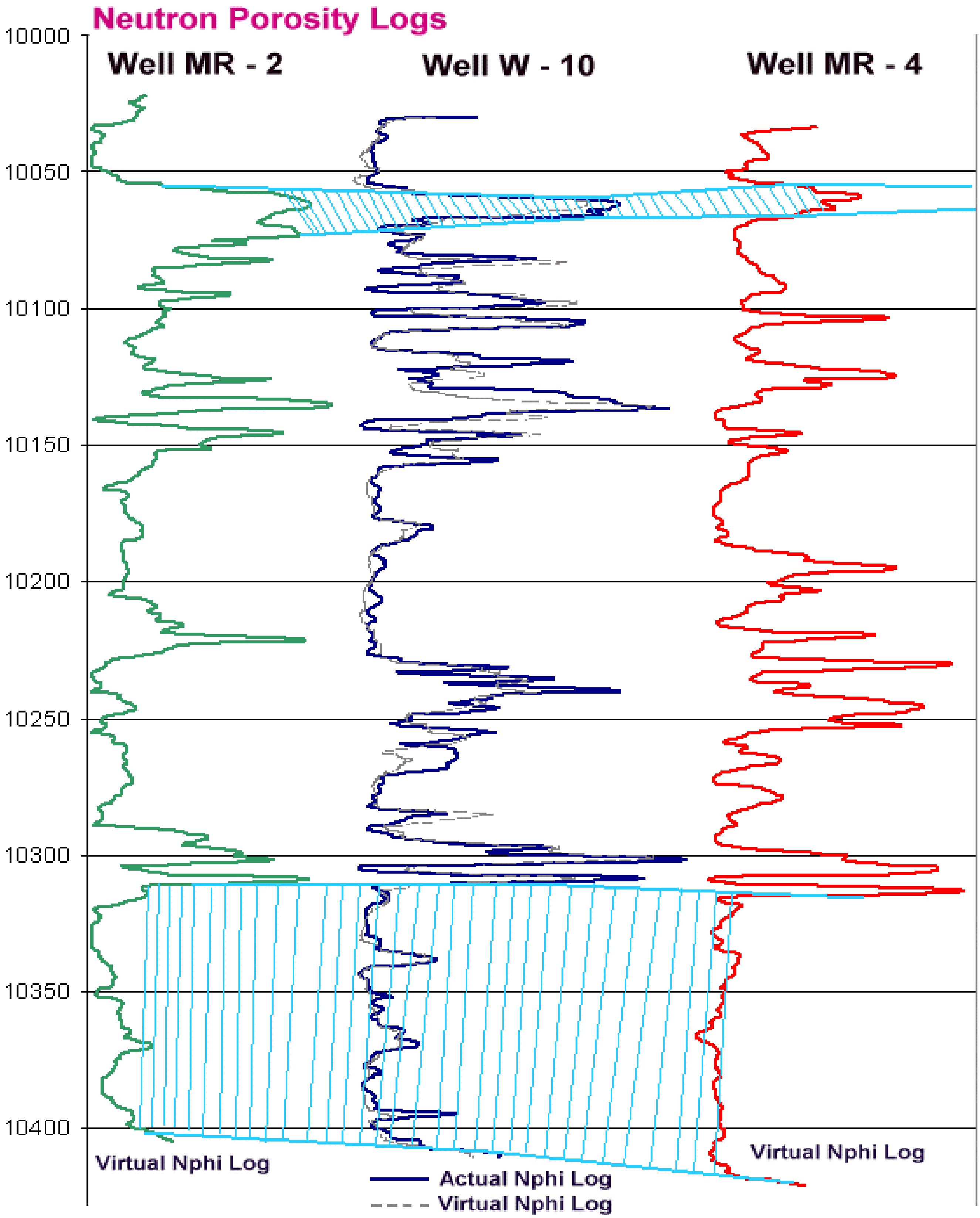

Figure 4. Actual and virtual neutron porosity logs for well W-10 along with virtual Nphi for wells MR-2 and MR-4.

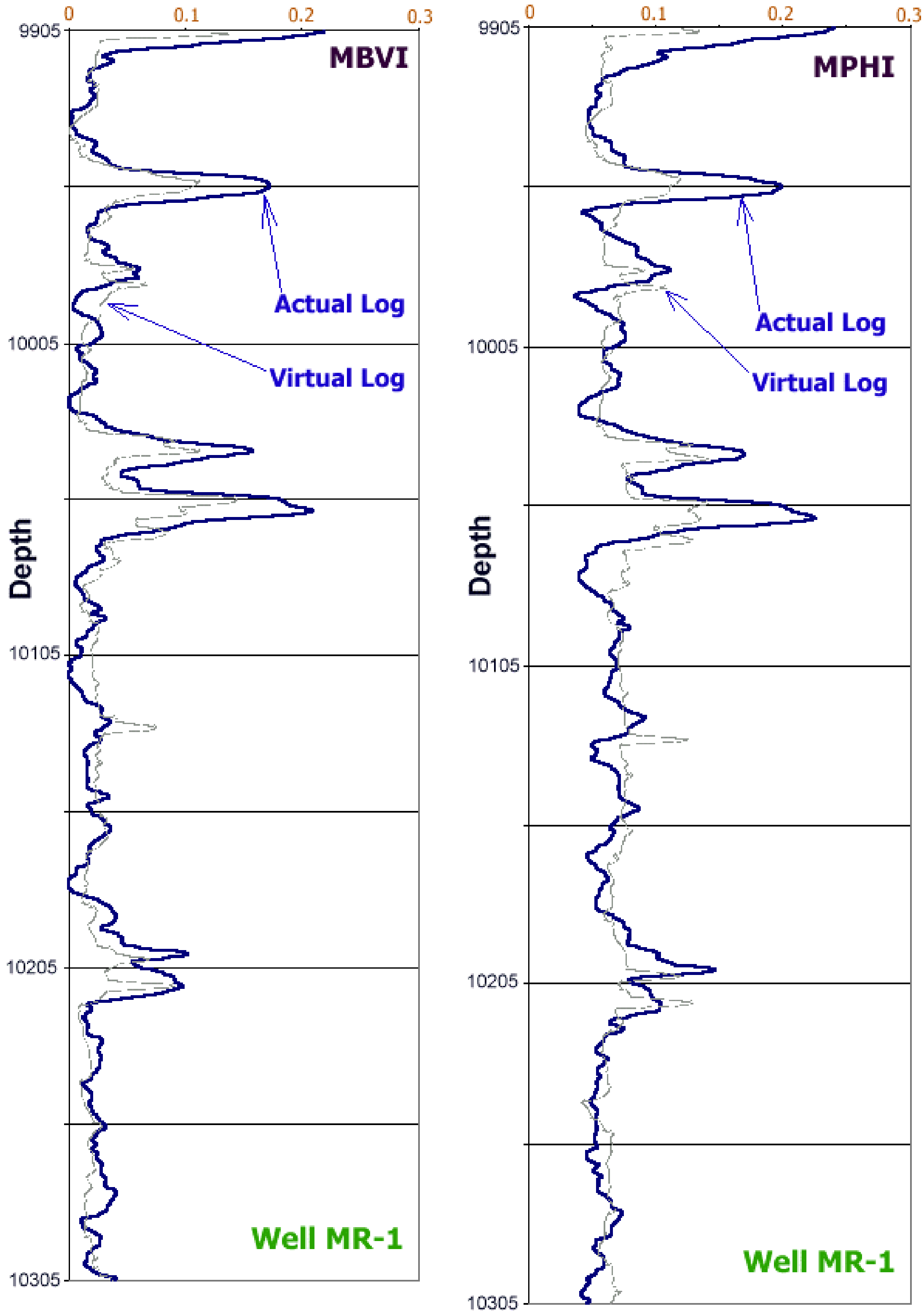

Figure 5. Actual and virtual magnetic resonance logs for well MR-1 along.

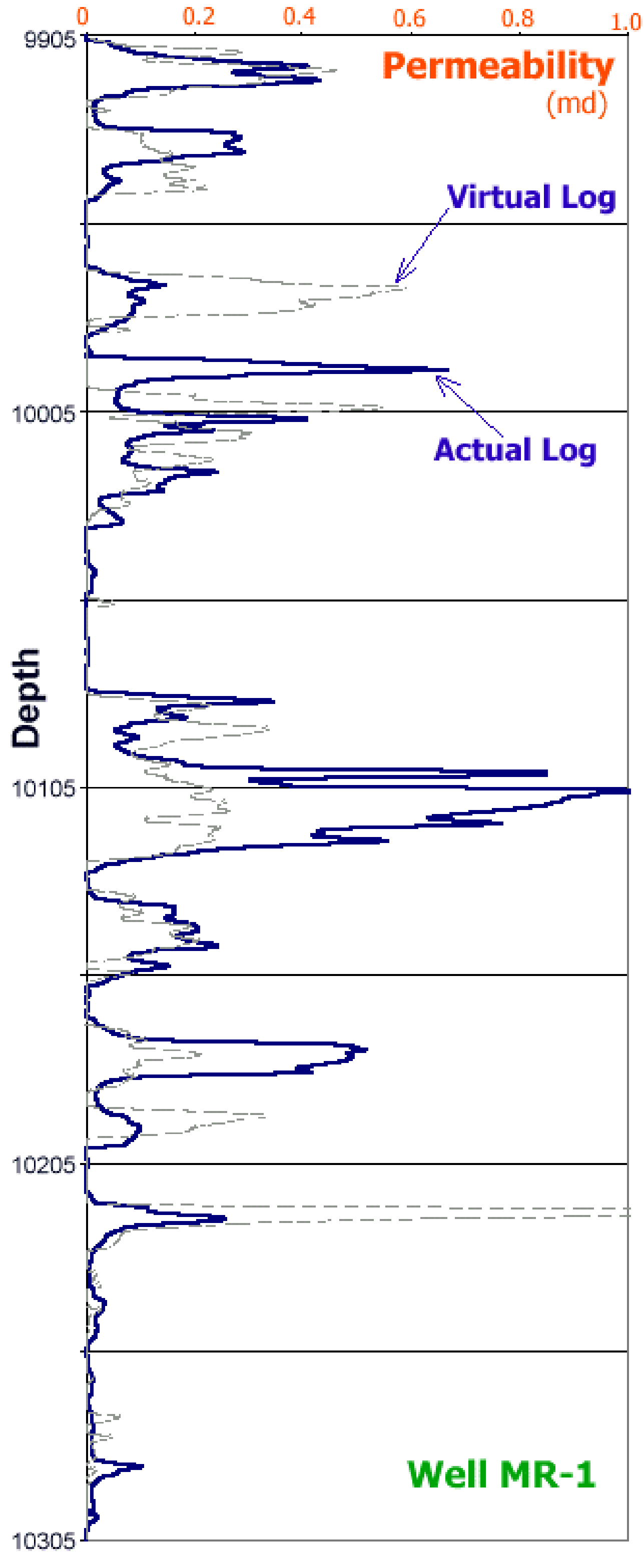

Figure 6. Actual and virtual magnetic resonance permeability logs for well MR-1 along.