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Chapter 27

VIRTUAL MAGNETIC RESONANCE LOGS, A LOW COST RESERVOIR DESCRIPTION TOOL

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ABSTRACT

Magnetic resonance imaging (MRI) logs are well logs that use nuclear magnetic resonance to accurately measure free fluid, irreducible water (MBVI), and effective porosity (MPHI). Permeability is then calculated using a mathematical function that incorporates these measured properties. This paper describes the methodology developed to generate synthetic magnetic resonance imaging logs using data obtained by conventional well logs such as spontaneous potential (SP), gamma-ray, caliper, and resistivity. The synthetically generated logs are named virtual magnetic resonance logs or 'VMRL' for short.

Magnetic resonance logs provide the capability of in-situ measurement of reservoir characteristics. 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 in two different fashions. First, it is applied to four wells; each from a different part of the country. These wells are located in East Texas, Gulf of Mexico, Utah, and New Mexico. Since only one well from each region is available, the model is developed using a segment of the pay zone and consequently is applied to the rest of the pay zone. In a second approach, the technique is applied to a set of wells in a highly heterogeneous reservoir in East Texas. Here the model was developed using a set of wells and then 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 reservoir description (effective porosity, fluid saturation, and permeability) and more realistic reserve estimation at a much lower cost.

1. INTRODUCTION

Austin and Faulkner (1993) published a paper in August 1993 in 'The American Oil and Gas Reporter' providing some valuable information about the Magnetic Resonance Logging technique and its benefits to low resistivity reservoirs.

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The MR log measures effective porosity – total porosity minus the clay bound porosity – as well as irreducible water saturation. The irreducible water saturation is the combinations of clay bound water and water held due to the surface tension of the matrix material. The difference between effective porosity (MPHI) and the irreducible water saturation (MBVI) is called the free fluid index. This is the producible fluid in the reservoir. This demonstrates how valuable MR log is to low resistivity reservoirs. In many low resistivity reservoirs, matrix irreducible water rather than producible water may cause a drop in resistivity. While producible water can seriously hamper production and make the pay quite unattractive, the same cannot be said for the irreducible water. Therefore, a reservoir that seems to be a poor candidate for further development – looking only at the conventional logs – may prove to be an attractive prospect once MR log is employed.

MRI logs may provide information that results in an increase in the recoverable reserves. This takes place simply by including the portions of the pay zone into the recoverable reserve calculations that were excluded during the analysis using only the conventional well logs. General background about neural networks has been published in numerous papers and will not be repeated in this paper. An example of such publications is included in the references Mohaghegh et al. (1995; 1996a,b; 1997).

As was mentioned earlier, in this study the developed technique is applied in two different ways. In the first attempt the author will show that it is possible to generate virtual magnetic resonance logs using conventional wireline logs. The concept is tested on several wells from different locations in the United States and the Gulf of Mexico. It is demonstrated that using artificial neural networks, it is possible to generate accurate virtual magnetic resonance logs. In this segment of the study part of the pay zone is used for the model development and then the model is tested on the rest of the pay zone. It is 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.

In the second attempt, which is considered to be the ultimate test for this methodology, it is tested in a manner that would simulate its actual use. This time data from several wells in a particular field is available. 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 are used for model development and consequent testing and verification of the model. Then the developed (and verified) model is 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 any study that requires accurate reservoir description such as, reservoir simulation, modeling, and reservoir management.

In the second part of this article, 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 (Mohaghegh et al., 1999) demonstrated the non-correlatable nature of formation characteristics and well logs in this formation.

2. METHODOLOGY

In this section the procedure and methodology for completing this study is explained. This section is divided into two parts. First, the methodology for the intra-well virtual magnetic resonance logs is covered. This is the first part of the study, where wells from different parts of the country are used to show the robustness of the methodology with respect to the type of the formation it is being applied to. The second part of this study is concentrated on one particular formation, Cotton Valley in East Texas. In this part, it is demonstrated that the methodology can be applied to a particular field and can considerably reduce the cost of reservoir characterization.

2.1. Wells from different formations

Four wells from different locations in the United States are used to demonstrate the development of virtual MRI logs. These wells are from East Texas, New Mexico, Utah, and Gulf of Mexico. These wells are from different formations and since the virtual MR methodology is a formation specific process, there was no option but to test the methodology using single wells. In this section, part of the pay zone will be used to develop the model and then the model is verified by using the remainder of the pay. The ideal way to show the actual potential of this methodology is to use several wells from the same formation (which also is presented in this article). The prerequisite is that both conventional and MRI logs for the wells should be available. In such a situation, a few of the wells would be used to develop the model and the remaining wells would be used for verification purposes.

For each well in this study, gamma-ray, spontaneous potential (SP), caliper, and resistivity logs were available. These logs were digitized with a resolution of six inches for the entire pay zone. Thirty percent of the data were chosen randomly for the model development and the remaining 70% of the pay were used for verification. In all four cases, the model was able to generate synthetic MR logs with correlation coefficients of up to 0.97 for data that was not used during the model development process.

The model development process was implemented using a fully connected; five layer neural network architecture with different activation functions in each layer. These layers included one input layer, three hidden layers and one output layer. Each of the hidden layers has been designed to detect distinct features of the model. A schematic diagram of the network architecture is shown in Fig. 1.

Please note that in this figure all of the neurons and/or connections are not shown. The purpose of the figure is to show the general architecture of the network used for this study. A supervised gradient descent backpropagation of error method was used to train the neural networks. The input layer has six neurons representing depth, gamma-ray, SP, caliper, medium and deep resistivity. Each hidden layer included five neurons. Upon completion of the training process, each neural network contained six weight matrices. Three of the weight matrices had 30 elements while the remaining matrices each had five. In most cases, acceptable generalization was achieved in less than 500 visits to the entire training data. Once the network was trained, it was used to generate the virtual MPHI, MBVI and MPERM logs. The MPHI and MBVI logs were then used to estimate

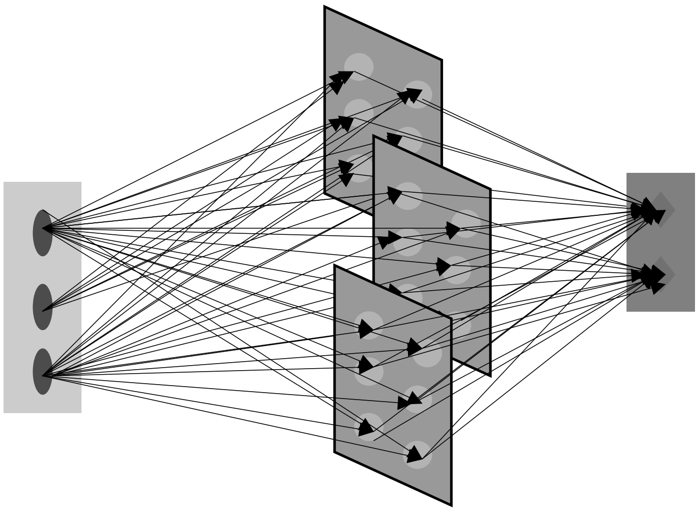

Fig. 1. Schematic diagram of the neural networks used in this study.

the reserves. In one case – the well in New Mexico – that was a tight reservoir, the resolution of the permeability data made it impossible to train an adequate network.

It should be noted that it might be more effective not to use a neural network to replicate the MPERM log. Since this log is derived from MPHI and MBVI, it would be better to calculate the virtual MPERM log from the virtual MPHI and MBVI.

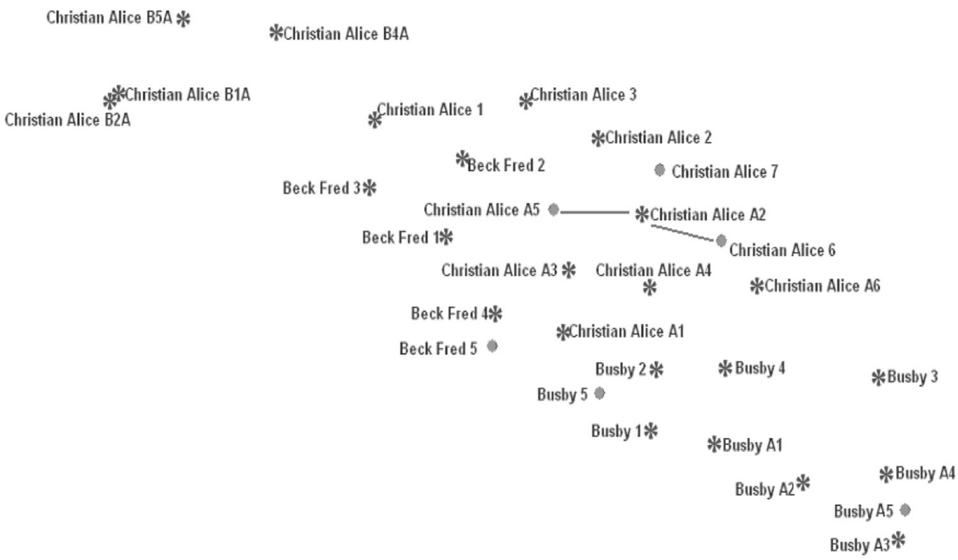

Fig. 2. Relative location of wells in the Cotton Valley, East Texas.

2.2. Wells from the same formation

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. Fig. 2 demonstrates the relative location of the wells. In this figure wells with magnetic resonance logs are shown with circles and wells that have no magnetic resonance logs are shown with asterisks. 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.

? Should type of logs in Table 1 be explained?

During the intra-well study, 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

TABLE 1

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

Well ID	CALI	SP	GR	ILD	ILM	SFL	NPHI	DPHI	RHOB	MBVI	MPERM	MPHI
Beck Fred 5	×	×	×	×	×					×	×	×
Chr. Alice A5	×	×	×	×	×	×				×	×	×
Chr. Alice A7	×	×	×	×	×	×				×	×	×
Chr. Alice 6	×	×	×	×	×	×				×	×	×
Busby 5	×	×	×	×	×					×	×	×
Busby A5	×	×	×	×	×					×	×	×
Chr. Alice B5A	×	×	×	×	×		×	×	×			
Chr. Alice B2A	×	×	×	×	×	×	×	×	×			
Chr. Alice B4A	×	×	×	×	×	×	×	×	×			
Beck Fred 1	×	×	×	×	×	×	×	×	×			
Chr. Alice 3	×	×	×	×	×	×	×	×				
Chr. Alice 2	×	×	×	×	×		×	×	×			
Beck Fred 4		×	×	×		×	×	×				
Chr. Alice A3		×	×	×			×	×				
Chr. Alice A1	×	×	×	×	×		×	×				
Chr. Alice A2	×	×	×	×	×	×	×	×	×			
Chr. Alice A4	×	×	×	×		×	×	×	×			
Busby 2	×	×	×	×	×	×						
Busby 1	×	×	×	×	×	×	×	×	×			
Busby A1	×	×	×	×	×	×	×	×				
Busby 4	×	×	×	×	×		×	×	×			
Chr. Alice A6	×	×	×	×	×	×		×				
Busby 2	×	×	×	×	×		×	×	×			
Busby 3	×	×	×	×	×	×	×	×	×			
Busby A4	×	×	×				×	×	×			
Busby A3	×	×	×	×	×	×	×	×	×			

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 co-dependency of input parameters to one another and removing those input parameters that are a function of others inputs.

A possible 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 Fig. 3.

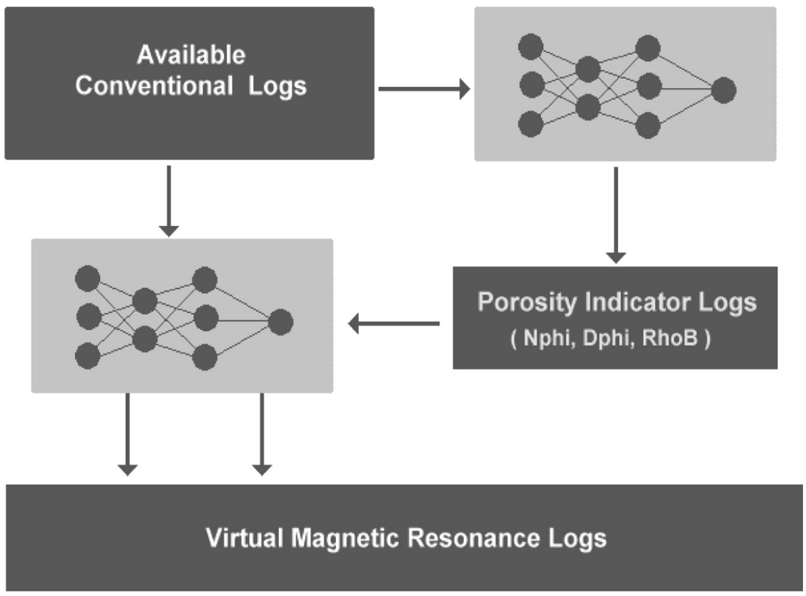

Fig. 3. Schematic diagram of the process for developing virtual magnetic resonance logs.

2.3. 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 Christian Alice A2 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. Fig. 4 shows the actual and virtual versions of all three logs (neutron porosity, density porosity, and bulk density) for the well Christian Alice A2.

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 Fig. 5. These wells (Christian Alice A5, Christian Alice 6 and Christian Alice A2) are in the proximity of each other. Christian Alice A5 and Christian Alice 6 did not have any conventional porosity indicator logs and well Christian Alice A2's conventional porosity indicator logs were not used during the model development process. Fig. 5 shows the virtual neutron porosity for all three wells as well as the actual neutron porosity for well Christian Alice A2. Formation signatures are easily detectable from all these wells. The distance between these wells Christian Alice A2 and each of the wells Christian Alice A5 and Christian Alice 6 is about 7000 ft. These distances are indicated with a line in Fig. 2.

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.

3. RESULTS AND DISCUSSION

Similar to the last section, results and discussions will also be presented separately for intra-well study and the study of the Cotton Valley field.

Figs. 6 and 7 show the actual and virtual MPHI, MBVI, and MPERM logs for the well in East Texas. Fig. 6 shows only the verification data set – data never seen by the network before – while Fig. 7 contains the virtual and actual logs for the entire pay zone. Virtual effective porosity log (MPHI) has a correlation coefficient of 0.941 for the verification data set and a 0.967 correlation coefficient for the entire pay zone. The values for virtual MBVI log are 0.853 and 0.894, respectively. The virtual permeability

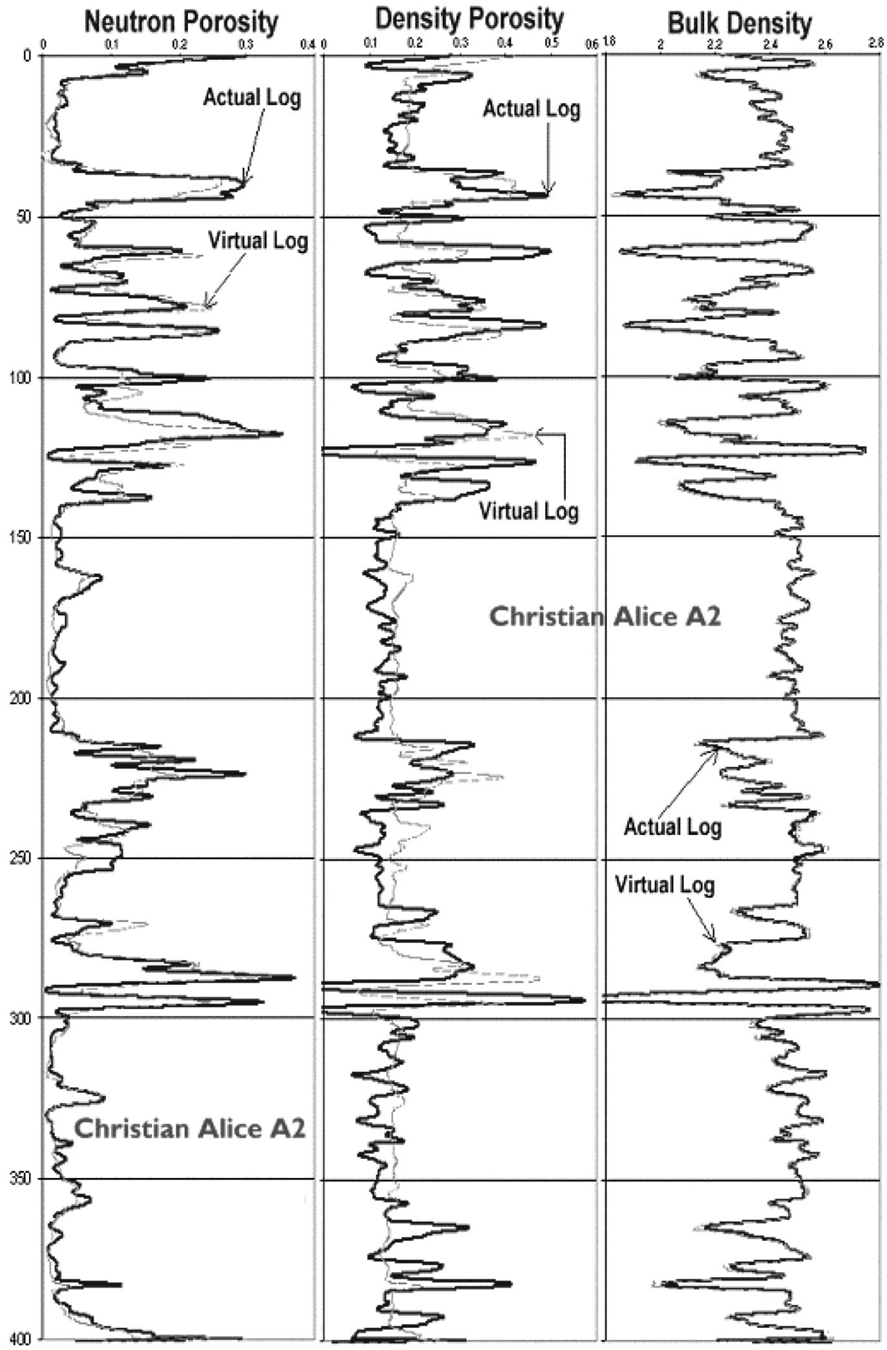

Fig. 4. Actual and virtual porosity indicator logs for well Christian Alice A2.

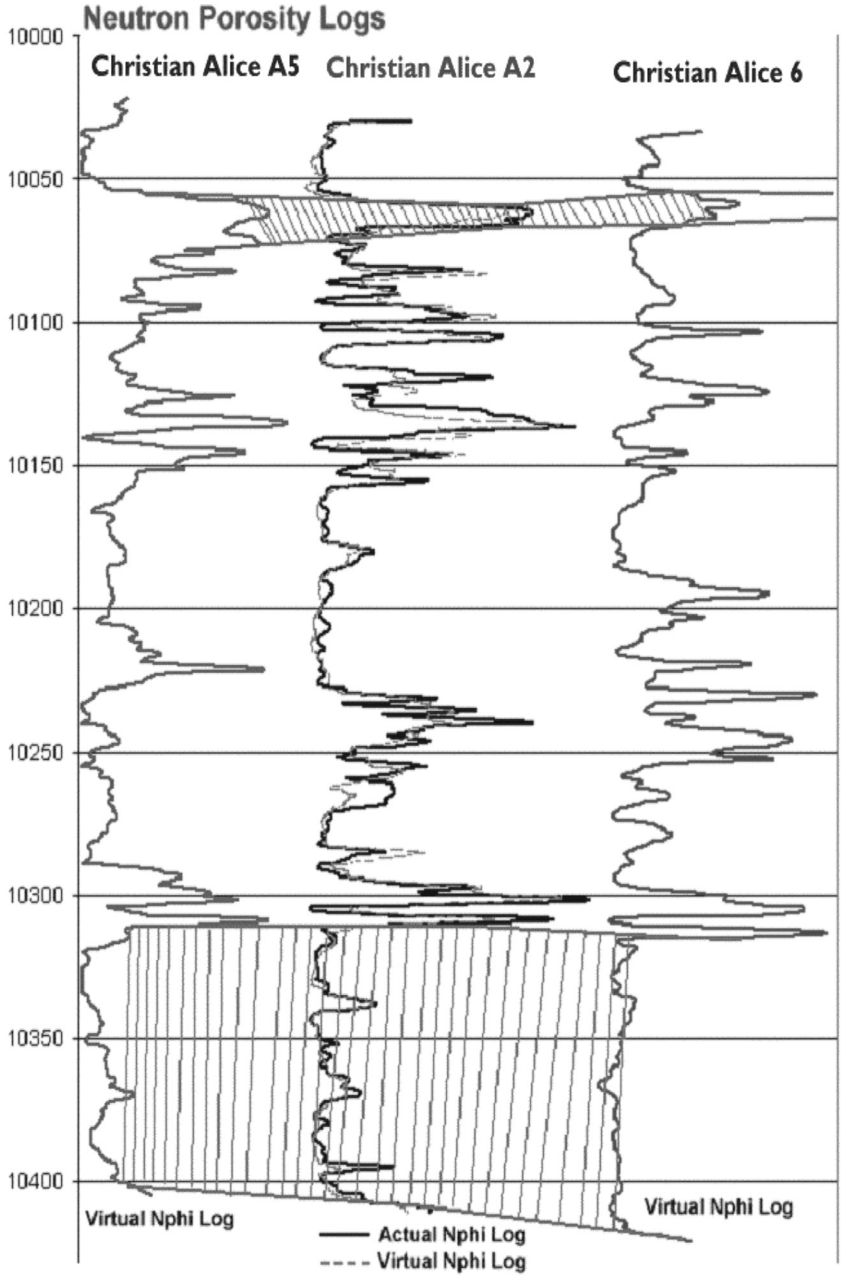

Fig. 5. Actual and virtual neutron porosity logs for well Christian Alice A2 along with virtual Nphi for wells Christian Alice A5 and Christian Alice 6.

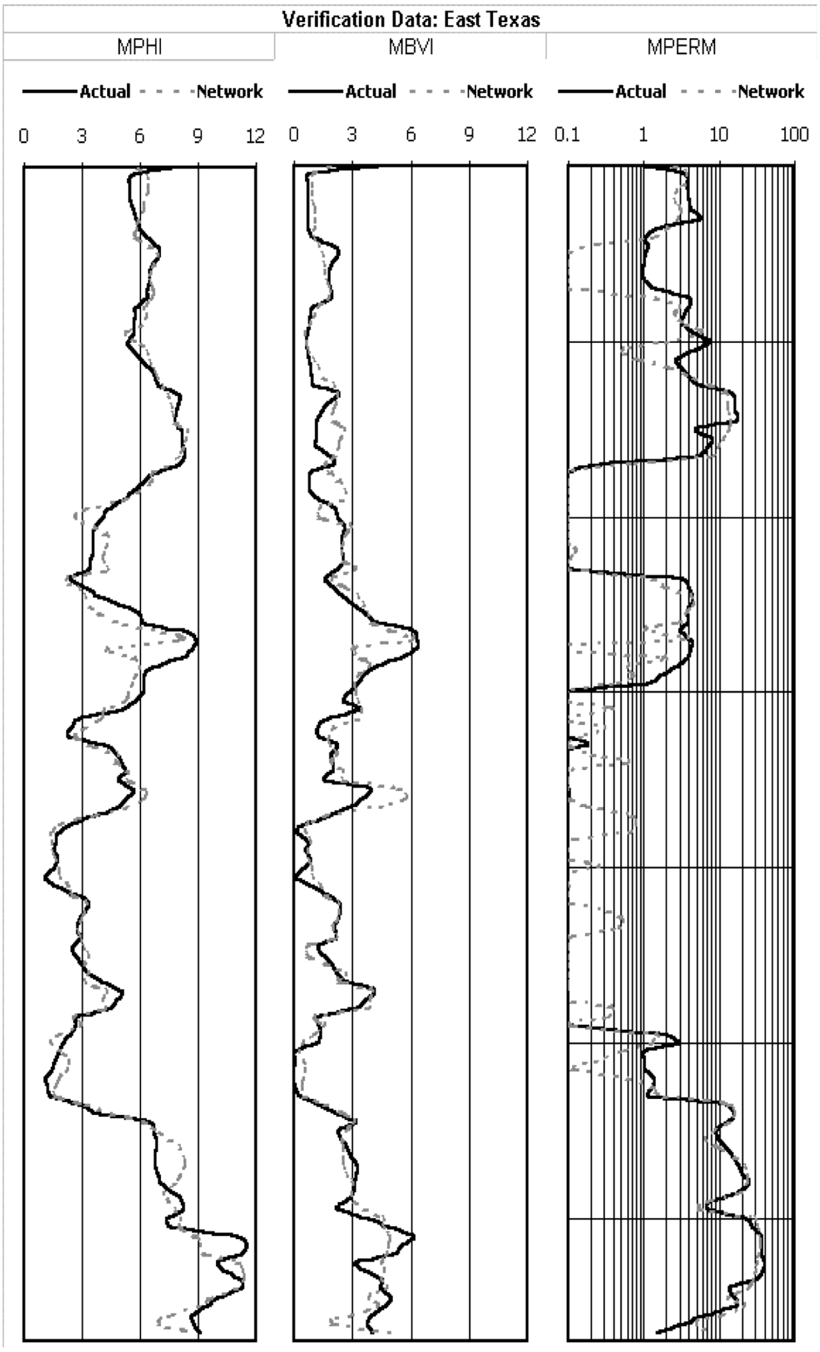

Fig. 6. Virtual and actual MRI logs for the verification data set for the well in East Texas.

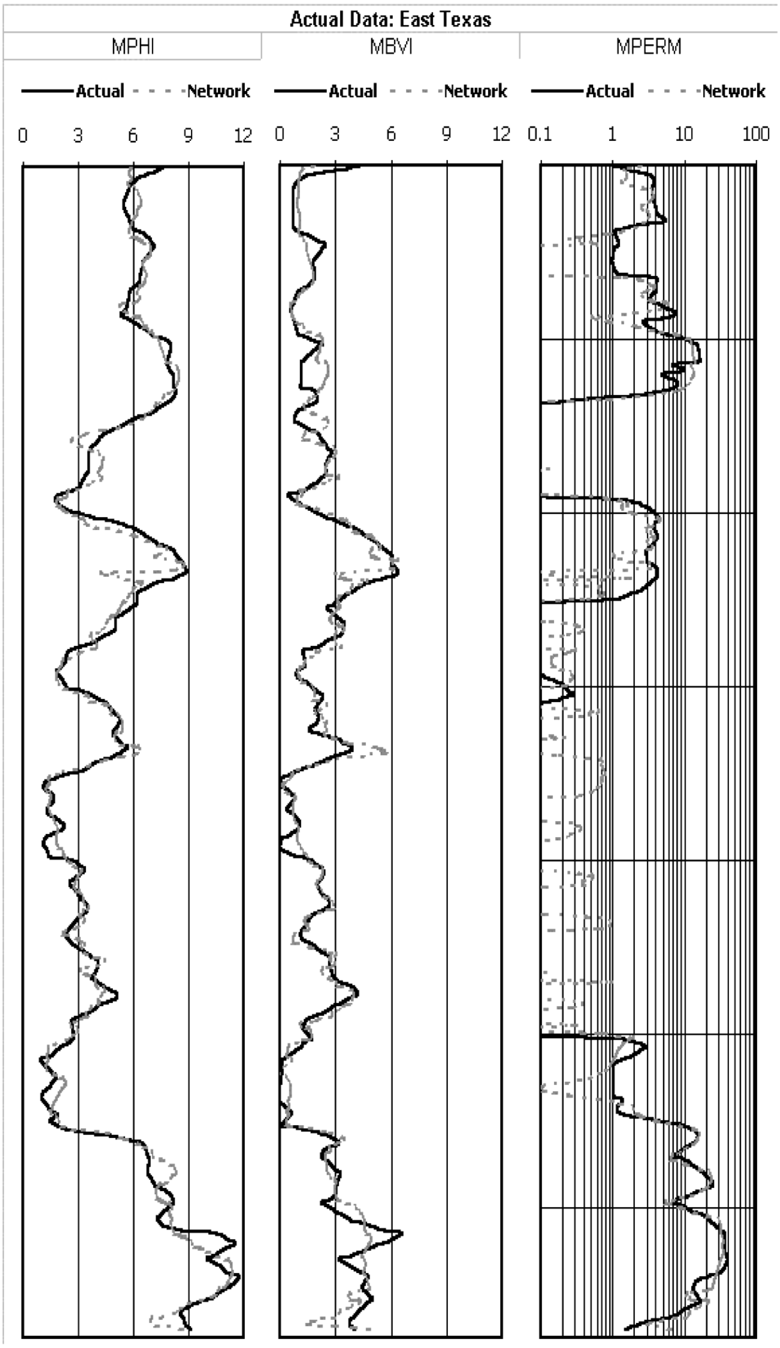

Fig. 7. Virtual and actual MRI logs for the entire pay zone for the well in East Texas.

log for this well also shows a strong correlation, 0.966 for the verification data set and 0.967 for the entire pay zone.

Figs. 8–13 show similar results for the wells from Utah, Gulf of Mexico, and New Mexico respectively. In all cases shown in these figures, virtual MRI logs closely follow the general trends of the actual MRI logs. Please note that MPERM logs are shown in logarithmic scale and therefore the difference in the lower values of the permeability can be misleading. The correlation coefficient provides a more realistic mathematical measure of closeness of these curves to one another.

Table 2 is a summary of the analysis done on all four wells. This Table contains the correlation coefficients for all the logs that were generated. This table shows the accuracy of the virtual MR log methodology on wells from different locations in the United States. The lowest correlation coefficient belongs to virtual MPHI log for the well located in Utah – 0.800 – while the best correlation coefficient belongs to virtual MPERM log for the well located in East Texas – 0.966.

Although the correlation coefficients for all the virtual logs are quite satisfactory, it should be noted that once these logs are used to calculate estimated recoverable reserves, the results are even more promising. This is due to the fact that many times the effective porosity and saturation is averaged. After all, MRI logs are used in two different ways.

TABLE 2

Correlation coefficient between actual and virtual MR logs for four wells in the United States

Well location	MR log type	Data set	Corr. coeff.
Texas	MPHI	Verification	0.941
		Entire Well	0.967
	MBVI	Verification	0.853
		Entire Well	0.894
	MPERM	Verification	0.966
		Entire Well	0.967
Utah	MPHI	Verification	0.800
		Entire Well	0.831
	MBVI	Verification	0.887
		Entire Well	0.914
	MPERM	Verification	0.952
		Entire Well	0.963
Gulf Of Mexico	MPHI	Verification	0.858
		Entire Well	0.893
	MBVI	Verification	0.930
		Entire Well	0.940
	MPERM	Verification	0.945
		Entire Well	0.947
New Mexico	MPHI	Verification	0.957
		Entire Well	0.960
	MBVI	Verification	0.884
		Entire Well	0.926

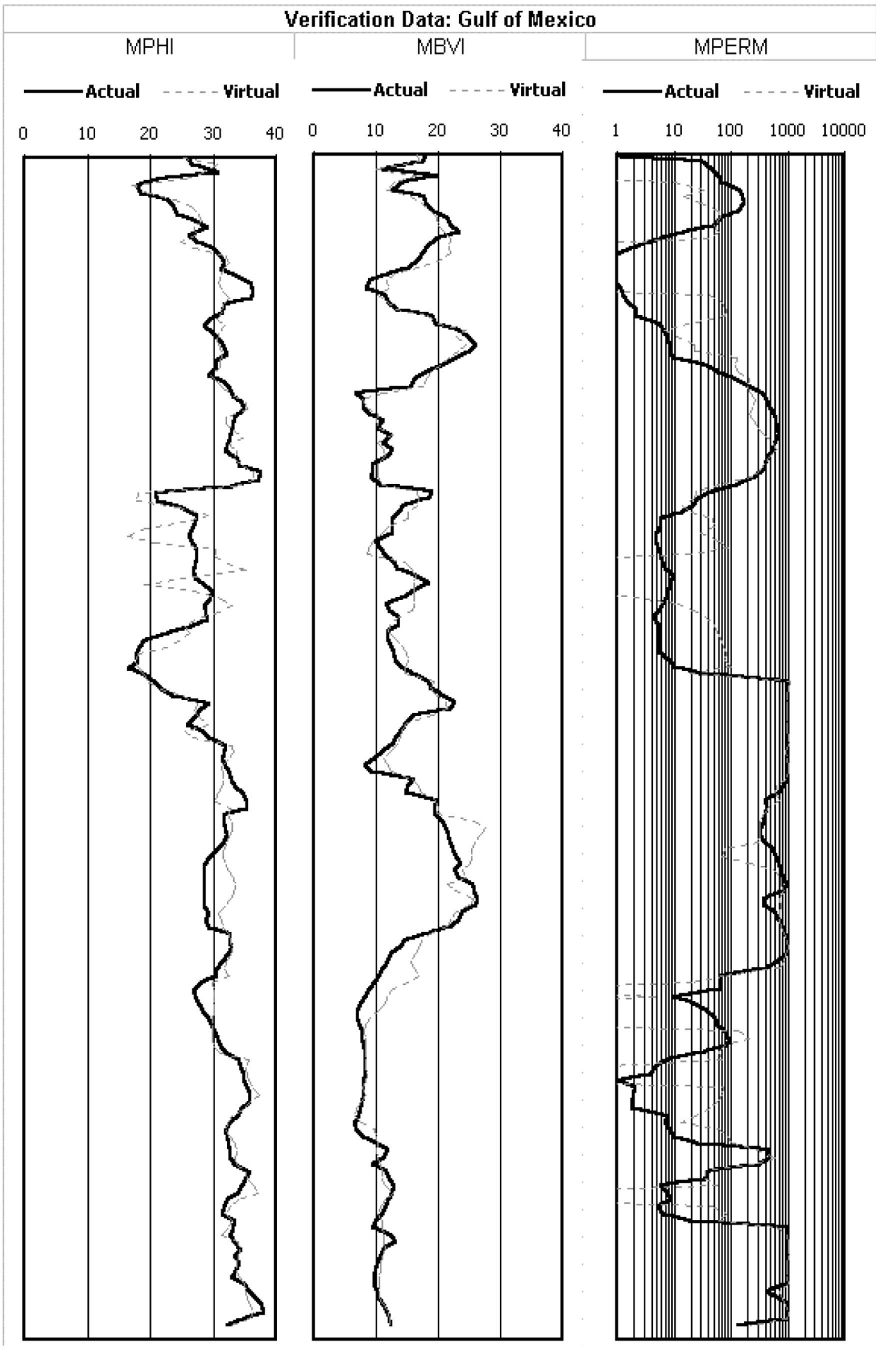

Fig. 8. Virtual and actual MR logs for the verification data set for the well in Gulf of Mexico.

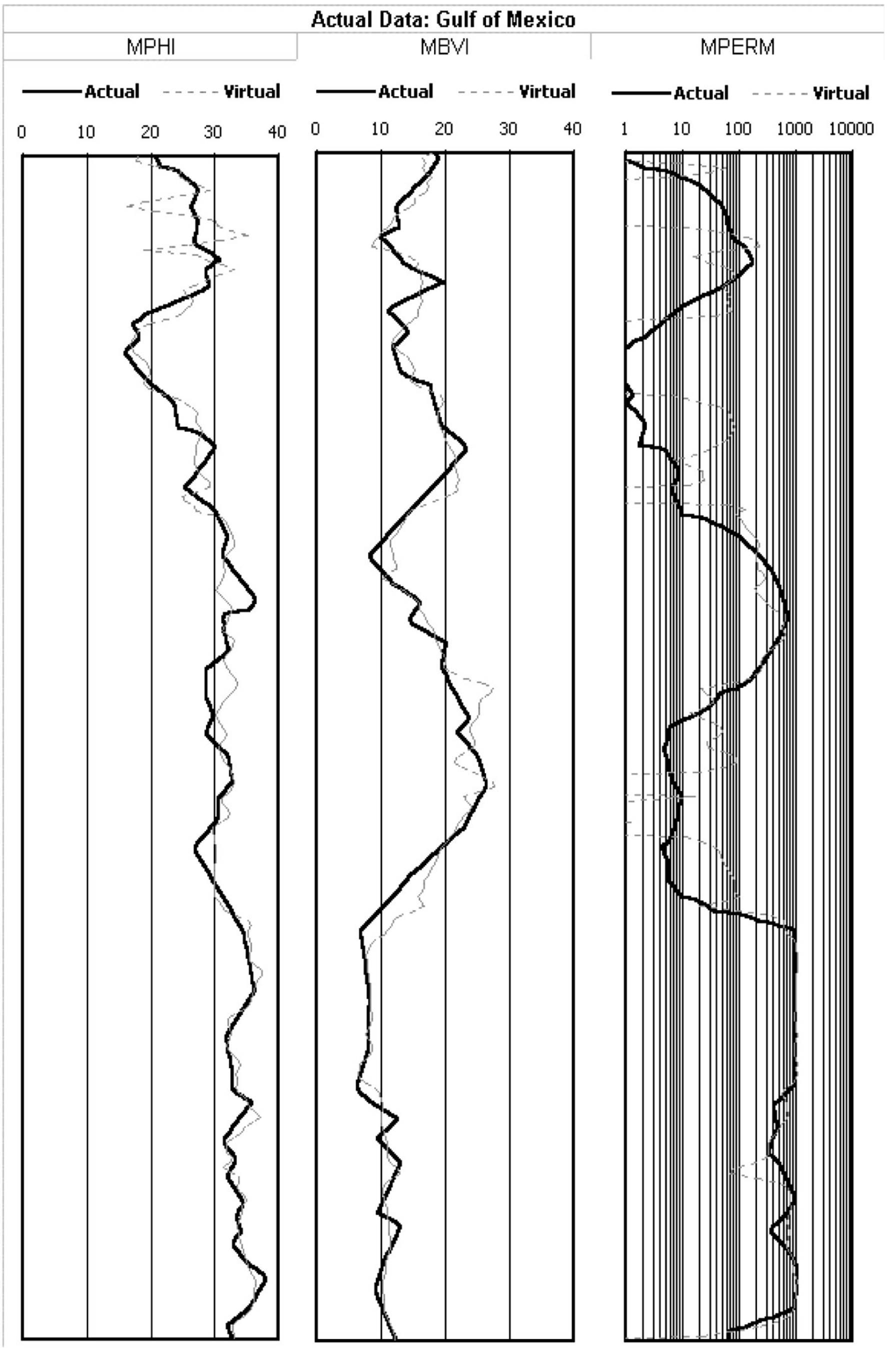

Fig. 9. Virtual and actual MRI logs for the entire pay zone for the well in Gulf of Mexico.

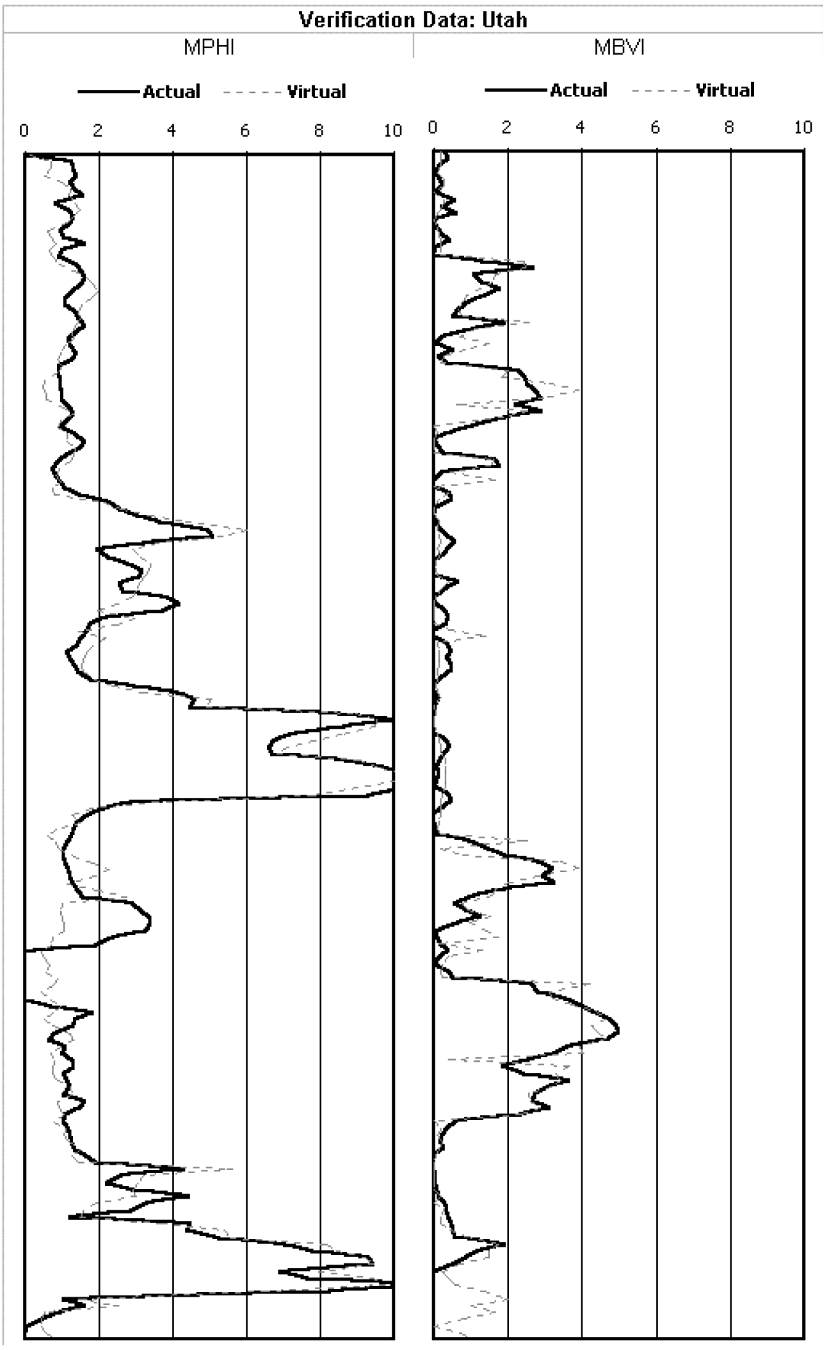

Fig. 10. Virtual and actual MRI logs for the verification data set for the well in Utah.

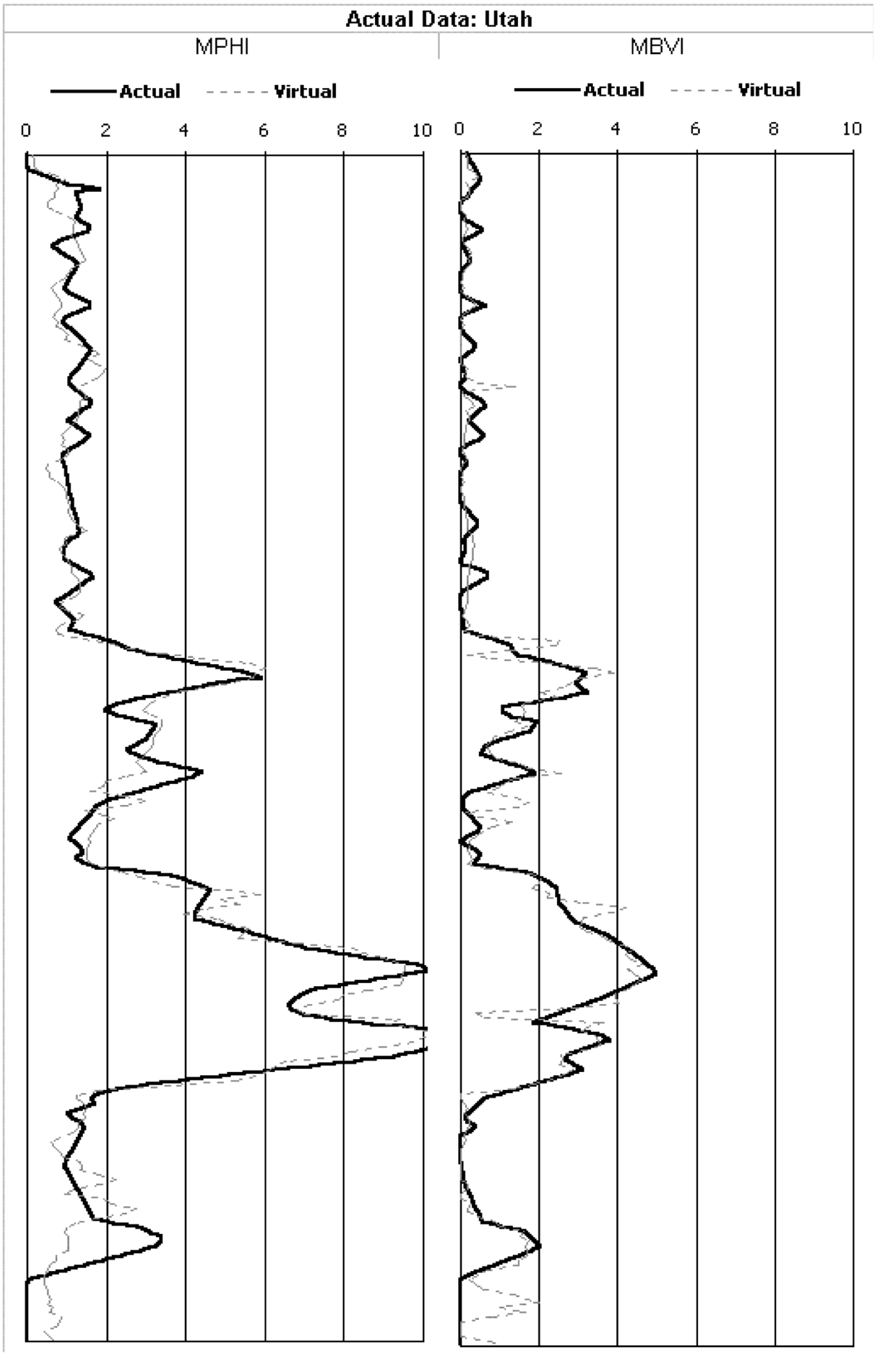

Fig. 11. Virtual and actual MRI logs for the entire pay zone for the well in Utah.

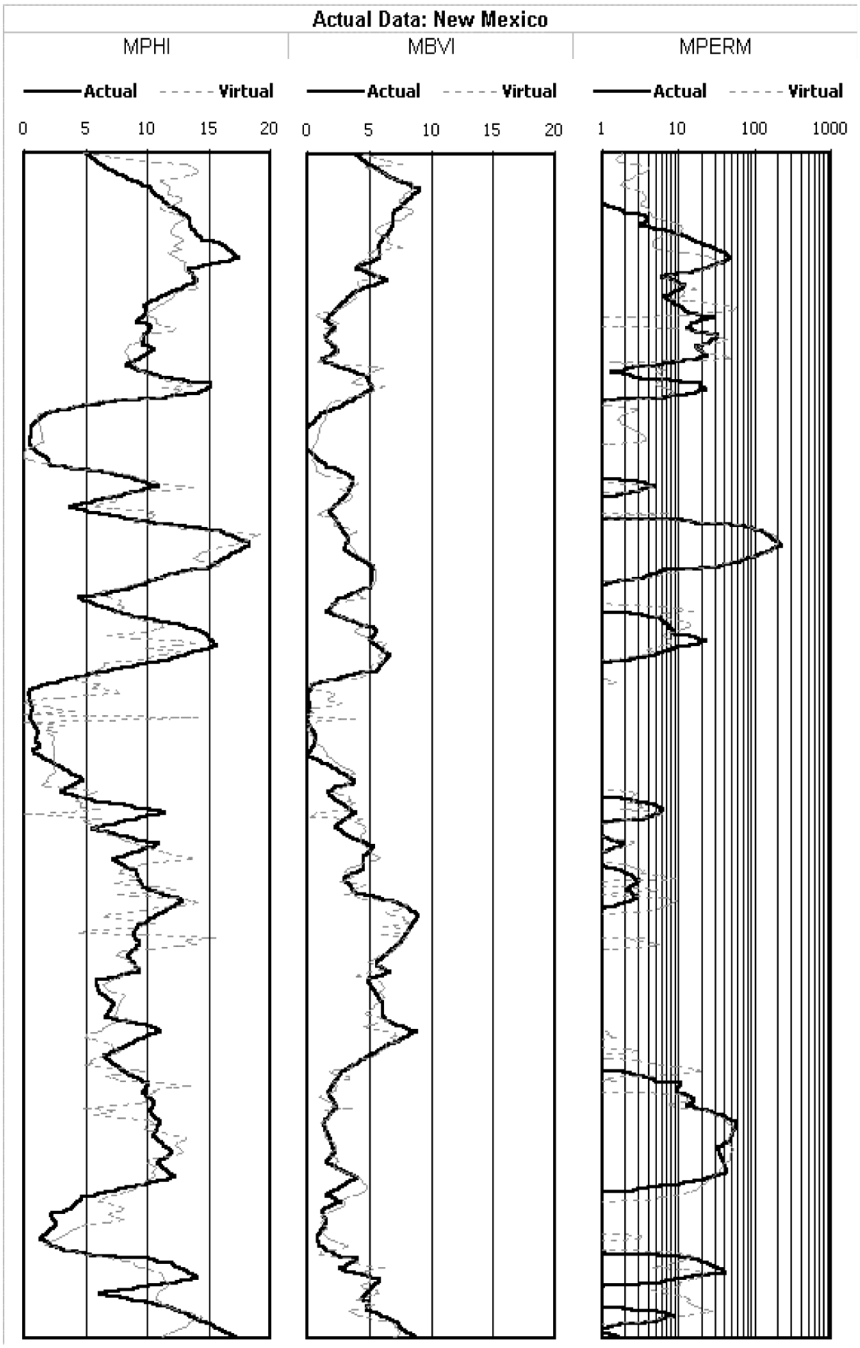

Fig. 12. Virtual and actual MRI logs for the verification data set for the well in New Mexico.

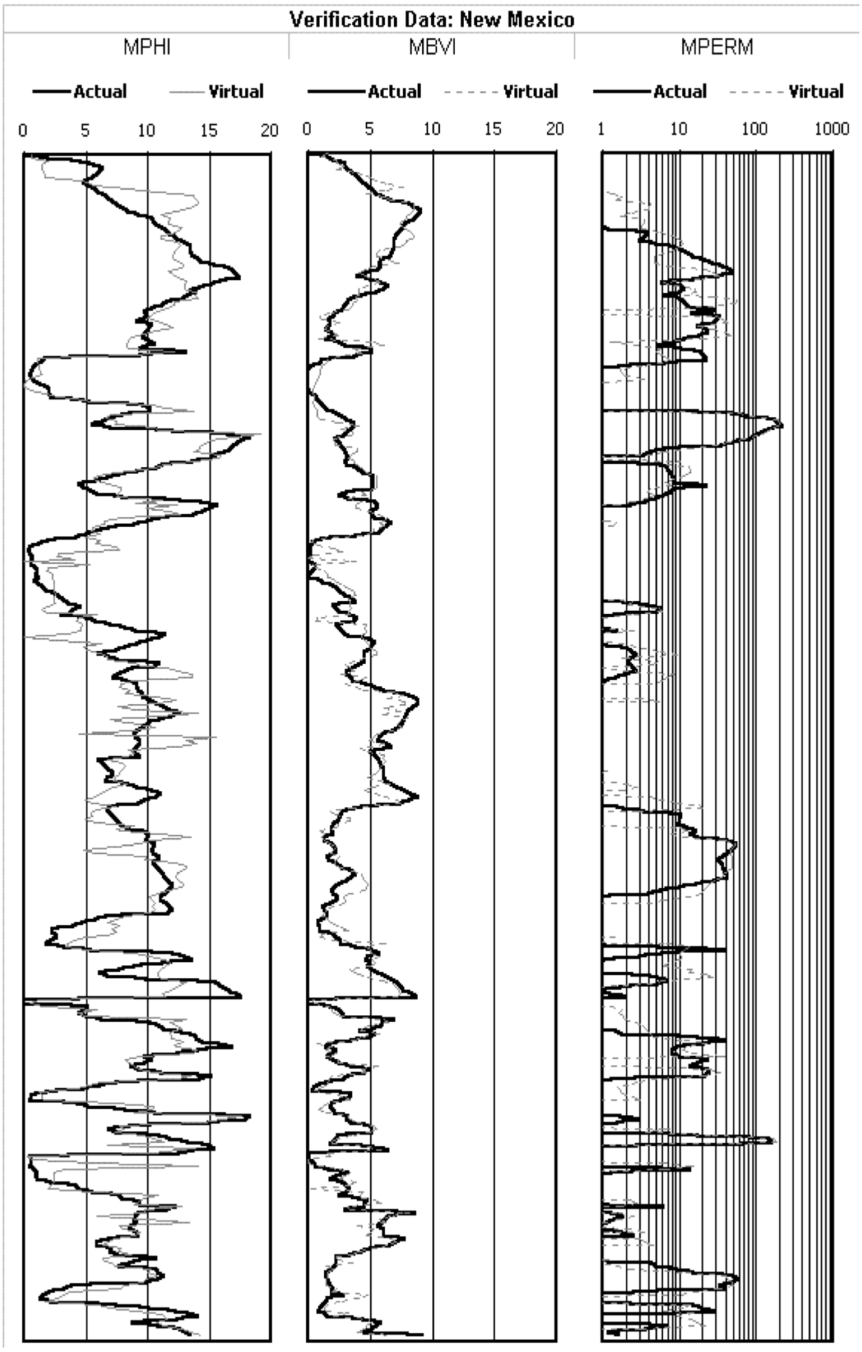

Fig. 13. Virtual and actual MRI logs for the entire pay zone for the well in New Mexico.

TABLE 3

A per-acre estimate of the recoverable reserves using actual and virtual MR logs for four wells in the United States

Well location	MR log type	Reserve Bbls/acre	Percent difference
Texas	Actual	52,368	−1.4
	Virtual	51,529	
New Mexico	Actual	24,346	−1.9
	Virtual	23,876	
Gulf of Mexico	Actual	240,616	+0.3
	Virtual	241,345	
Utah	Actual	172,295	−1.8
	Virtual	169,194	

One-way is to locate and complete portions of the pay zone that have been missed due to the conventional log analysis. This is more a qualitative analysis than a quantitative one since the engineer will look for an increase in the difference between MBVI and MPHI that correspond to a high permeability interval. The second use of these logs is to estimate the recoverable reserves more realistically.

The reserve estimates calculated using virtual MRI logs when compared to estimates calculated using actual MRI logs were quite accurate. As shown in Table 3, the reserve estimates using virtual MRI logs ranged from underestimating the recoverable reserves by 1.8% to over estimating it by 0.3%.

Figs. 14–17 show the virtual and actual MR logs for wells in East Texas and the Gulf of Mexico. These logs are shown in the fashion that MRI logs are usually presented. These logs clearly show the free fluid index – difference between MBVI and MPHI logs – and the corresponding permeability values. This particular representation of the MRI logs is very useful to locate the portions of the pay zone that should be completed. The parts of the pay that has a high free fluid index and corresponds to a reasonably high permeability value are excellent candidates for completion.

So far it was demonstrated that this methodology presented here is a viable tool for generating virtual magnetic resonance logs for different formations. 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

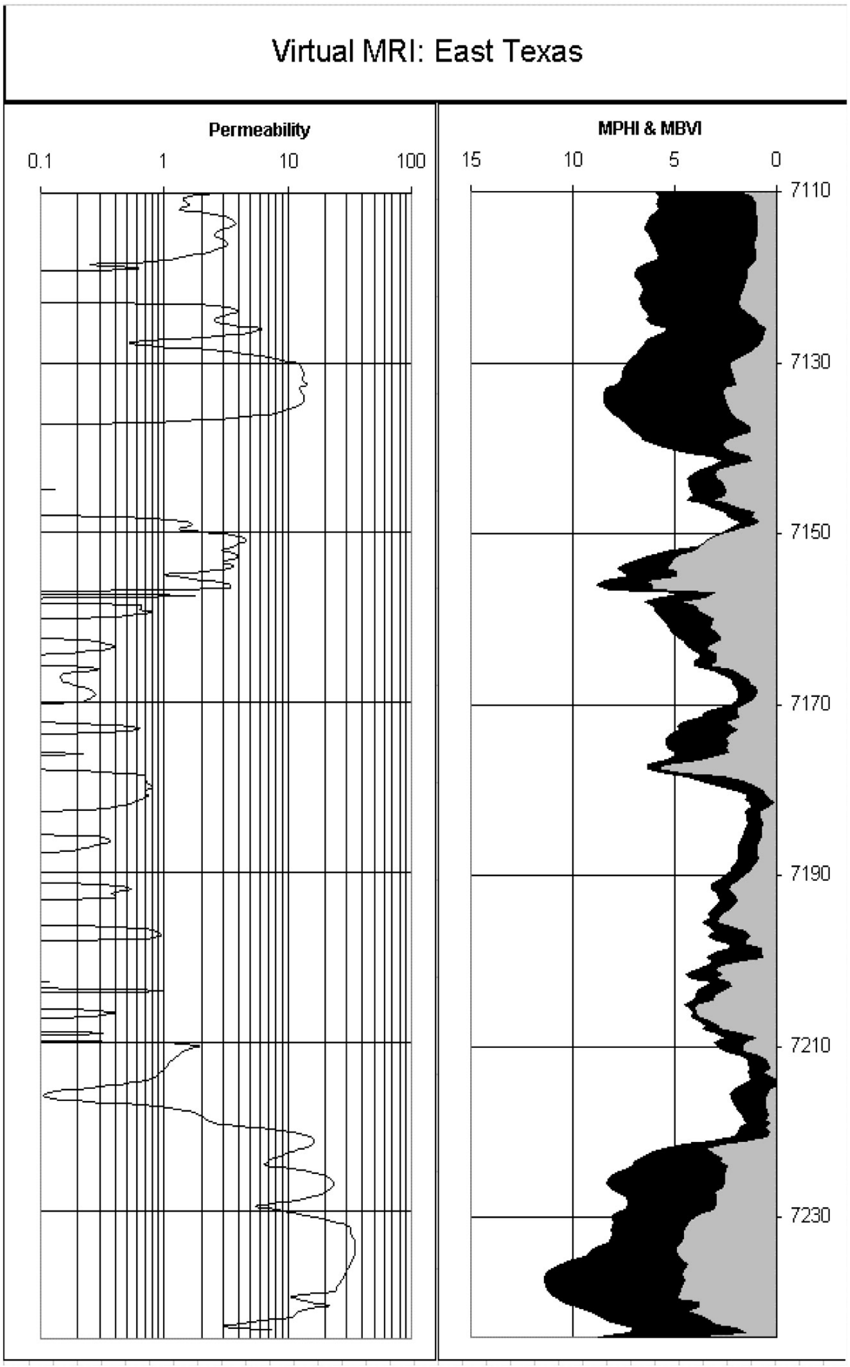

Fig. 14. Virtual MR logs for the well in East Texas

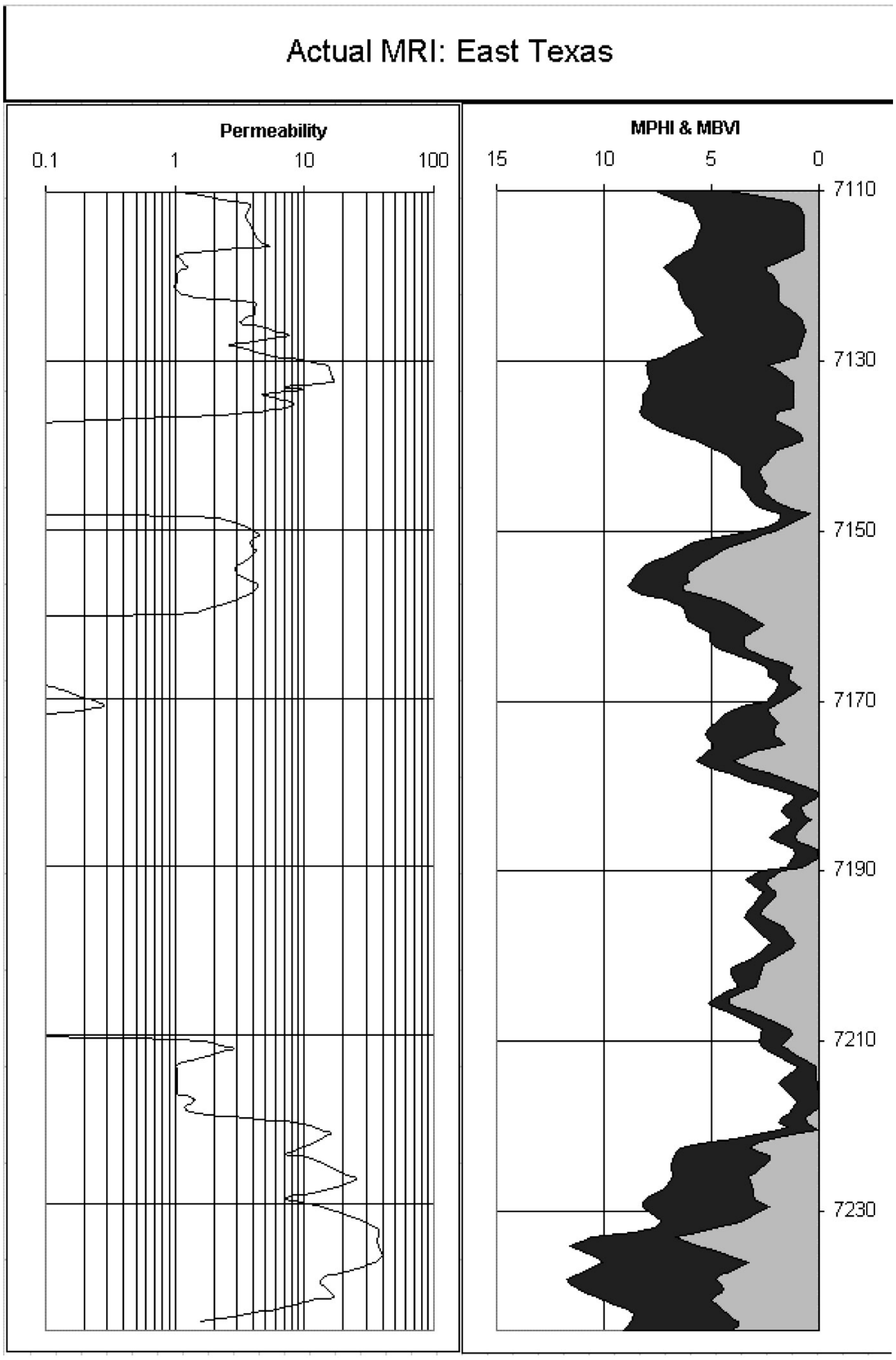

Fig. 15. Actual MR logs for well in East Texas

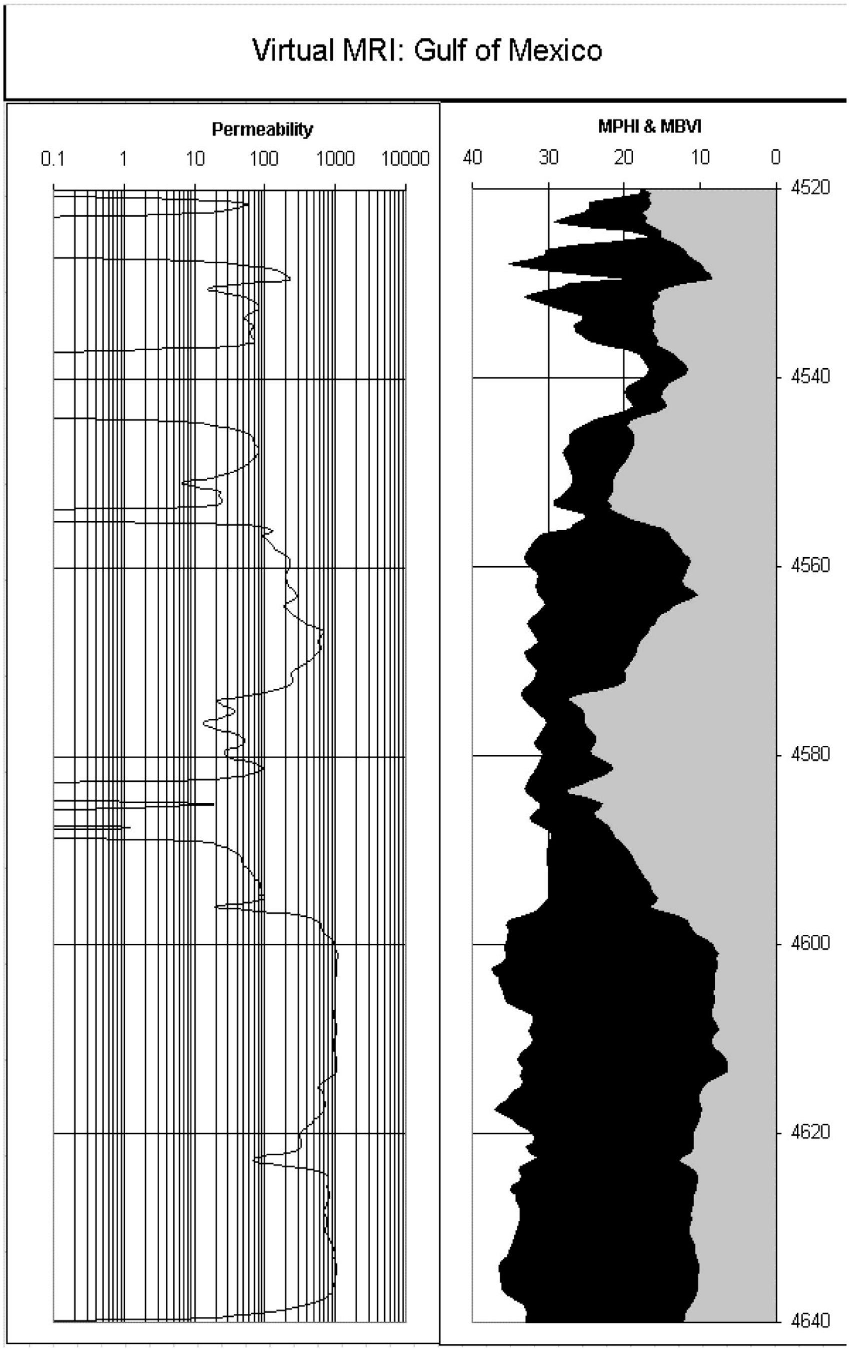

Fig. 16. Virtual MR logs for the well in Gulf of Mexico.

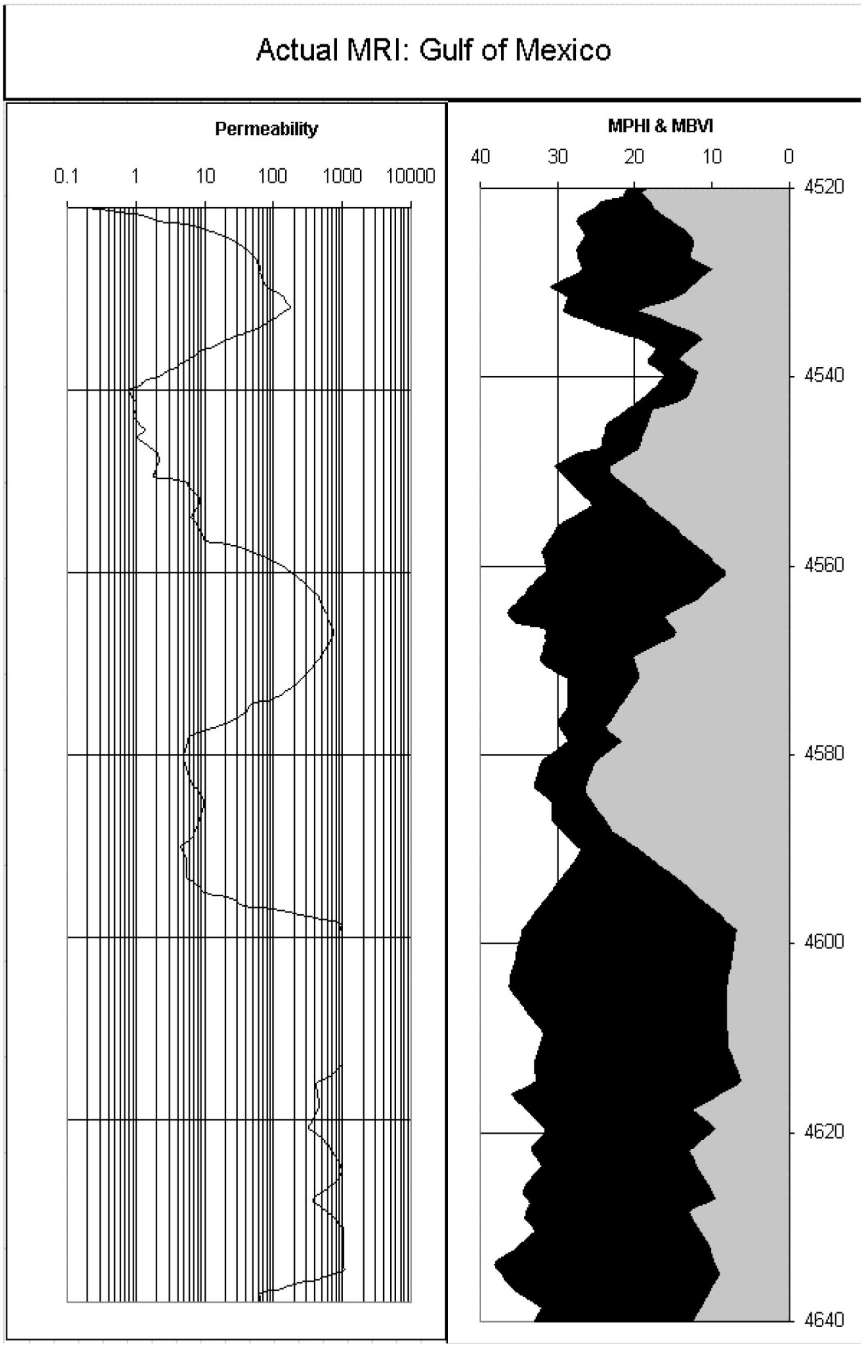

Fig. 17. Actual MR logs for the well in Gulf of Mexico.

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 Fig. 2, 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 portion of this article. During this process we demonstrate that the methodology of generating virtual magnetic resonance logs is a valid and useful process in a field-wide basis. We demonstrate this by using five of the wells, Christian Alice A5, Christian Alice 2, Christian Alice 6, Busby A5, and Busby 5, to develop an intelligent, predictive model and generate virtual magnetic resonance logs for well Beck Fred 5. Since the magnetic resonance logs for well Beck Fred 5 are available, but not used during the model building process, it would provide an excellent verification well. Furthermore, since well Beck Fred 5 is on the edge of the section of the field being studied, and is somewhat outside of the interpolation area, relative to wells Christian Alice A5 . . . Busby 5 (the five wells with magnetic resonance logs), 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.

Fig. 18 shows the actual and virtual magnetic resonance logs (MPHI – effective porosity, and MBVI – irreducible water saturation) for well Beck Fred 5. 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.

Fig. 19 shows the actual and virtual magnetic resonance permeability logs – MPERM – for the same well (Beck Fred 5). 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

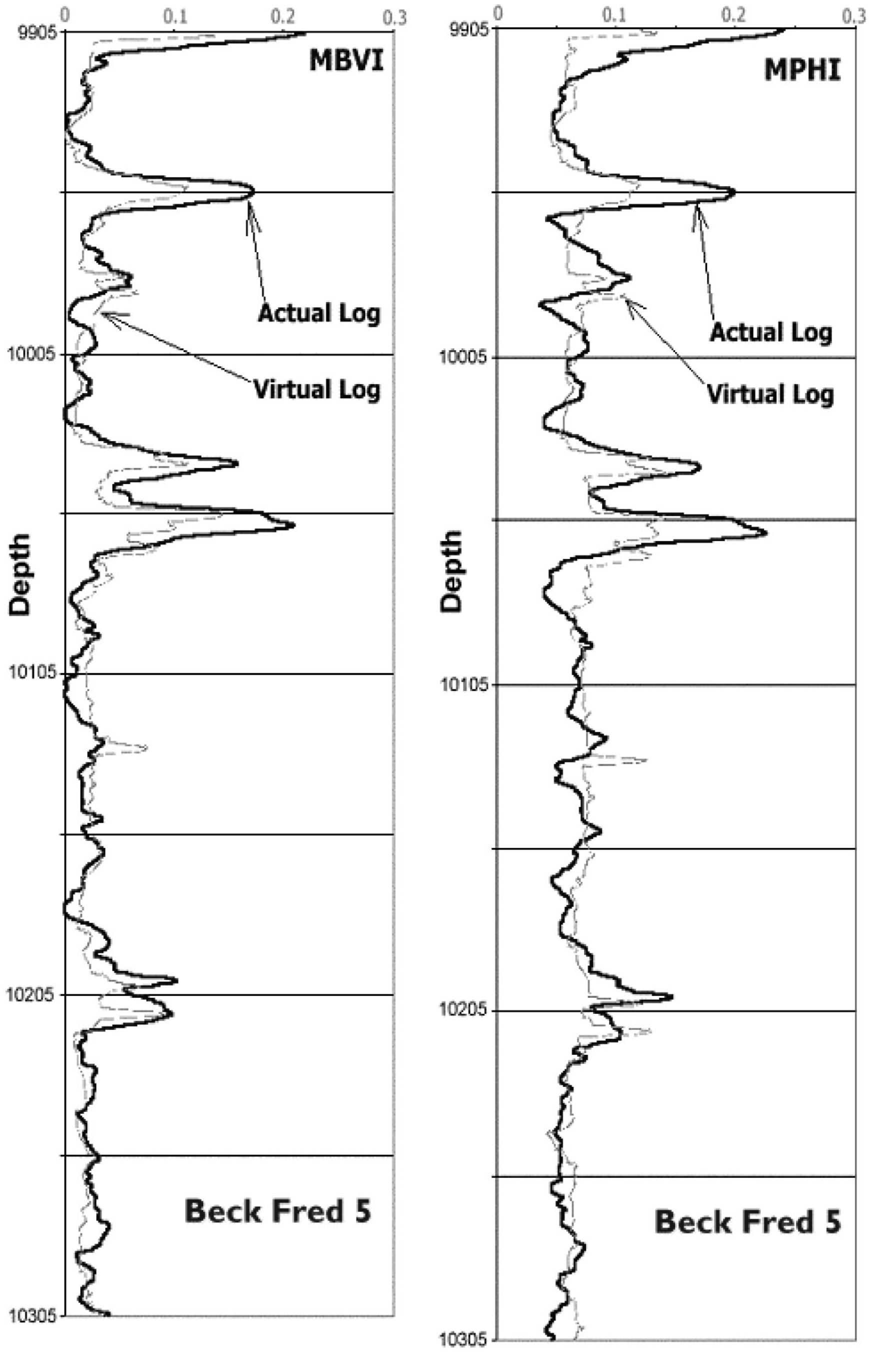

Fig. 18. Actual and virtual magnetic resonance logs for well Beck Fred 5.

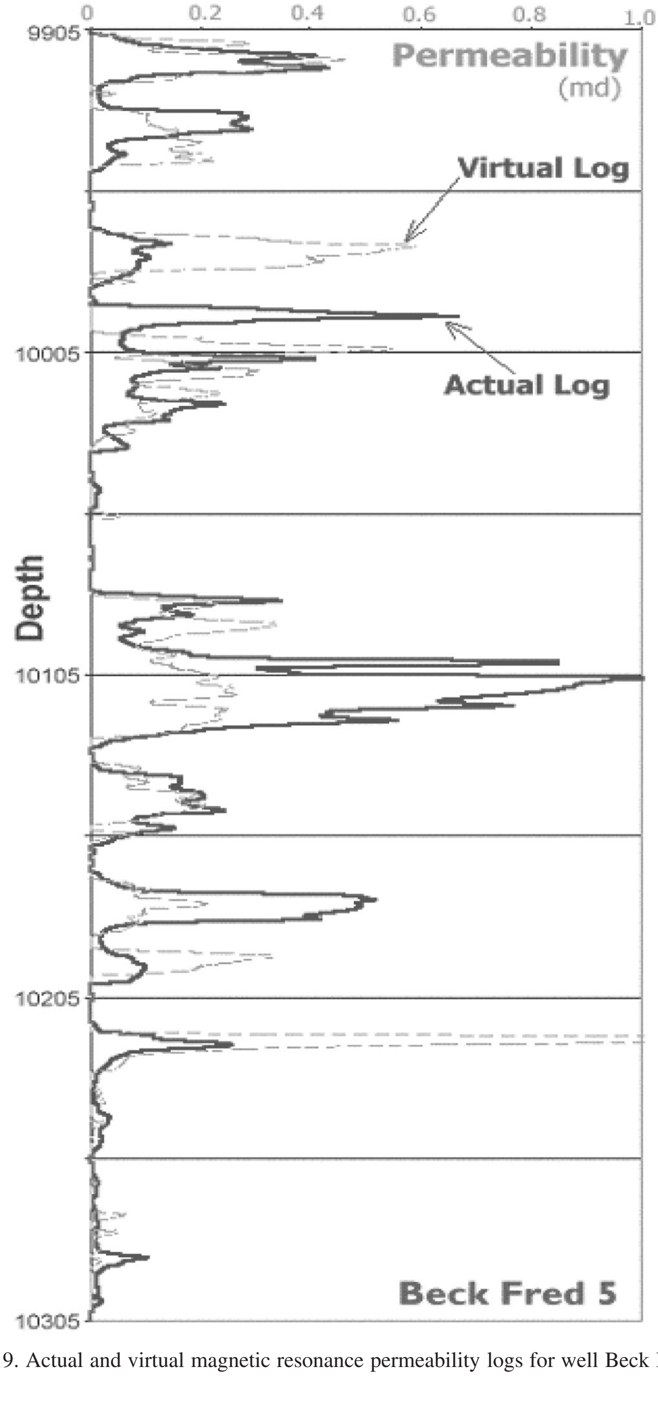

Fig. 19. Actual and virtual magnetic resonance permeability logs for well Beck Fred 5.

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 Fig. 18 are used to perform 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 400 ft 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.

4. 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. The neural networks that are constructed and trained for a particular formation may not be used to generate virtual MR logs for other formations. This is similar to the case of virtual measurement of formation permeability the methodology is formation dependent (Mohaghegh et al., 1996a).

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