Integrated Approach for Reliable Estimation of Permeability Profiles- A Case Study of L-II Reservoir of Mumbai High

Bhag Chand Jain*, Dev Singh, Aditya Kumar[1] and Chaman Lal[2]

KDMIPE, ONGC, Dehradun

[1] Assam Asset, ONGC, Nazira, Assam

ONGC, Mehsana

Summary

For generation of permeability relation, Alternating Conditional Expectation (ACE) [1,2] method which is based on non-parametric regression technique is used in this paper. This method quantitatively integrates information for core measured permeability data with log parameters like gamma ray, effective porosity, bulk density, resistivity and volume of clay of a well to estimate relation for permeability profiles generation. For selecting the reliable relation from ACE method for the generation of best permeability profile use of at-a-glance view of the various data sets approach is suggested here.

Various log parameters used for estimating the relation for permeability profile generation, water saturation log data, core permeability data, generated permeability profile data, permeability data from pressure transient methods, perforation interval, and zone type details for L-II reservoir were plotted in standard format well-wise to have glance view of various data set.

Glance view of the information provides an integrated picture. It facilitates selection of the most representative relation by matching the well history (through critical analysis of generated permeability profile) with all the other plotted data prior to its finalization. In this process optimization of a number of log parameters as well as core data set points is primarily based on history match instead of earlier used approach in which it was based upon best co-relation coefficient value, mathematically. Using this approach, permeability profile was generated for wells of L-II reservoir, MH Asset, Mumbai, India. This knowledge helped in better reservoir management and optimized oil production.

Introduction

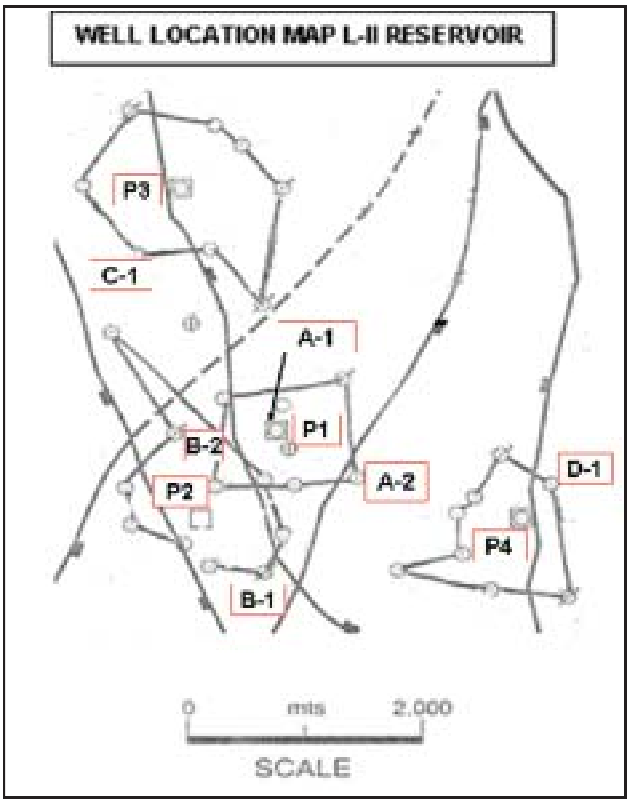
Due to complex nature of oil/gas reservoirs, interpretation of permeability data is generally affected by the inherent boundary conditions in the models used to interpret it. For better understanding of the internal framework of the reservoirs, critical analysis of information derived from different ways (that means under different boundary conditions) by integrating various kind of data set is very much required. This indicates more stress on integrated approach to construct 'the most probable permeability model' of a reservoir for effective reservoir management. In case of carbonate/complex reservoirs, the presence of fractures/complications makes the task much more difficult.

In oil industry parametric regression methods are generally used for permeability profiling. In this approach *a priori* knowledge of functional relationship between dependent variable and independent variable is required. For example popularly used Timur equation considers effective porosity and irreducible water saturation (swi) log parameters only for estimating permeability. As another example popularly used Kozney Carman equation also uses effective porosity and surface area per unit grain volume (sv) parameters for estimating permeability. Surface area per unit grain volume parameter is directly proportional to swi in this equation. This indicates in such type of popular approaches only few log parameters are considered even with a limitation of *a priori* knowledge of functional relationship between dependent variable and independent variable for permeability profile generation.

In presence of fractures/other complications, effective porosity as well as irreducible water saturation (swi) log data may not be having good correlation with permeability. It means known relationship between known and unknown variables also does not hold good which is the backbone for parametric regression methods. So profiling of permeability from above the methods is affected badly in presence of fractures/other complications.

To overcome these problems in this study not only an attempt is made for permeability profiling using non-parametric regression approach-*ACE* but also selection of most representative relation for generating permeability profiles is made through at-a-glance view approach described here. This approach involves history of the wells in selection of the best relation. Using ACE method more petrophysical parameters can be used without *a priori* knowledge of functional relationship between dependent variable and independent variables for better integrated picture. The method of ACE constructs and modifies the individual transformations to achieve maximum correlation in transformed space as well as provides better integrated approach in terms of log data.

The reservoir under study is a limestone reservoir named as L-II reservoir. This pertains to MH Asset, Mumbai, India. L-II reservoir is the second largest oil bearing limestone reservoir of this asset. L-II reservoir is mainly divided into L-II A & L-II B sub layers. From hydrocarbon point of view mainly L-II B reservoir is interesting and is further divided in six zones named as A, B, C, D, E and F. Location map with changed platform/well names for the platform/wells used here in this paper is given in figure-1. First letter indicates platform name and the others indicates well number.



Fig,.1: Well location map for the wells discussed.

Method

Various log parameters (like gamma ray, effective porosity, bulk density, resistivity and volume of clay of a well) used for estimating the relation for permeability profile generation, water saturation log data, measured core permeability data, generated permeability profile data, permeability data from pressure transient methods, perforation interval, and zone type details for L-II reservoir were plotted in standard format well-wise to have glance view of various data set. For critical analysis various other data from the history of the well like injection data / production data / PLT data was kept in mind for each well under critical analysis using the glance view plots.

Many times this type of integration helps in pin-pointing the limitations of individual data set so that values from other data set may be appreciated. Use of this approach involves the history of the wells in the relation developed for permeability estimation prior to the final selection of it. As in this process optimization of a number of log parameters as well as core data set points is primarily based on history match instead of earlier used approach in which it was based upon best co-relation coefficient value, mathematically.

After many attempts good history match in some of the wells particularly the well for which the core measured permeability data is considered as in this case well P1A-1 was obtained with five log variables for k prediction using ACE, based on *at-a-glance* view approach. These five log variables are: gamma ray (Gr), effective porosity (Φ_e), bulk density (ρ_b) resistivity (R_{lld}) and volume of clay (V_{clay}). The data set used to generate transform for k prediction consists of above mentioned log variables and core measured k from well P1A-1. For efficient integration of core data and log data for well P1A-1 necessary depth shift in core depth has been considered to have best matching between the depths of well logs and coring depth.

The optimal transformations for permeability with five selected well log variables were obtained. Also sum of transformed well log variable is constructed. Finally, permeability is predicted from well log data using the following equations derived by ACE algorithm:

$$\ln(k)=-2.8145E-01x2+2.0187E+00x+2.3055E+00 \quad (1)$$

where ,

$$x = Sum\_Tr = Gr\_Tr + \Phi e\_Tr + \rho b\_Tr + Vcl\_Tr + \ln(Rlld)\_Tr$$

and

$$Gr\_Tr = 6.2683E-04\ (Gr)^2+1.7437E-01\ Gr - 5.1983E+00$$
$$\Phi e\_Tr=2.5576E+01(\Phi e)^2- 1.1777E\ 00\ \Phi e -1.4239E+00$$
$$\rho b\_Tr=4.8395E+01(\rho b)^2 - 2.0478E+01\rho b +2.1466E+00$$
$$Vcl\_Tr=4.4318E+01\ (Vcl)^2 -1.6915E+01Vcl + 6.7246E-01$$
$$\ln(Rlld)\_Tr = -2.1529E-01\ \ln(Rlld)^2 + 1.2656E+00\ \ln(Rlld) -1.6498E+00$$

Using these equations permeability values for well P1A-1 as well as other wells has been predicted using the individual well log data set for complete section point to point for L-II reservoir.

For selecting the best relation developed for generating permeability profile which satisfies most of the history of the well, at-a-glance view of the data sets approach suggested here is demonstrated through figure-2. Figure-2 shows the integrated at-a-glance view of various data sets to see degree of match between measured and ACE estimated k-values for complete L-II reservoir interval with the available details from the history of the well P1A-1 collected at different point of times. In changed well names, first letter reflects the platform name and the second the well number.

Figure-2 is self explanatory and clearly reflects the very good match of estimated permeability values not only with the core measured permeability values but also the values from pressure transient methods at different point of time for the intervals as indicated in figure-2. This figure-2 also indicates that the permeability values estimated reflects better picture of variations which are having a support from some of the log data plotted/history of the well, rather a constant value from pressure transient data which is generally the limitation due to boundary conditions for interpretation most of the time.

At present this well is transferred after producing oil & gas from L-II reservoir to some other gas sand (sand-I) reservoir. This is below the L-II reservoir. However the history indicates some salient point for L-II reservoir which can be explained very well with the profiles generated for L-II reservoir as shown in figure-2.

-Water cut abruptly increased to 65% (Sep-95), after some time of adding the bottommost layer (991.5-994 m) in July-94. Very near the bottom most layer perforated high water saturation layers are present. In initial phase of production these high water saturation layers were responsible for water production because these are having good permeability conditions as revealed by the profiles generated.

- During tracer test, tracer break-through was observed in two years from well P2B-1 to P1A-1 (Apr-96 to Jan-98). This observation supports the above view (time taken in tracer break-through explains injected water could not be produced initially in well P1A-1).
- In later phase of production due to presence of relatively high permeability streaks, as revealed by the generated permeability profiles in both the wells, water from injector dominated for water production in this well (preferential water movement from P2B-1(zone-D) to P1A-1 (zone-D)).

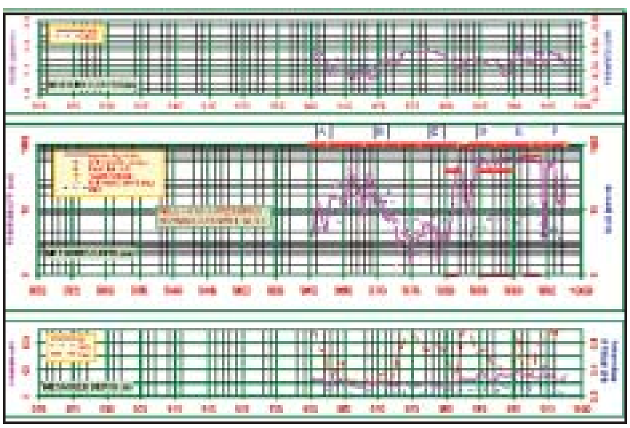


Fig. 2 : At-a-glance view of various data sets; Well- P1A-1

To have more confidence prior to finalization of the relation developed many other wells were tested using at-a-glance view of the data sets approach suggested here for the history match. Out of these one more example from central part from different platforms of the L-II reservoir from where major production is coming is given in figure-3, for well P3C-1which is also self explanatory. Presently this well is completed in L-II reservoir and is flowing oil.

Figure-3 shows the integrated at-a-glance view of various data sets to see degree of match between measured and ACE estimated k-values for complete L-II reservoir interval with the available details from the history of the well P3C-1 collected at different points of time. This plot clearly reflects very good match with pressure transient derived values for permeability in various intervals.

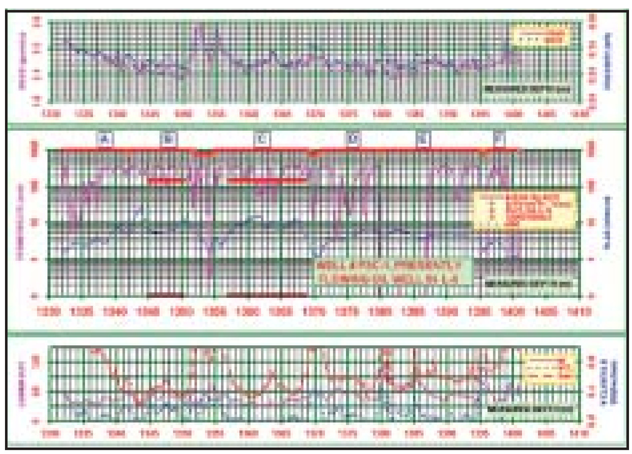


Fig. 3: At-a-glance view of various data sets; Well- P3C-1

After testing the relation developed with well data through at-a-glance view of the data sets approach described here it is essential to see the match on point to point basis between estimated and core measured values for well P1A-1.

Figure-4 shows the very good match between core measured and estimated k-values for the interval in which core data is available in well P1A-1selected by using at-a-glance view of the data sets approach. This indicates very good match for permeability values in the interval where core measured data is available.

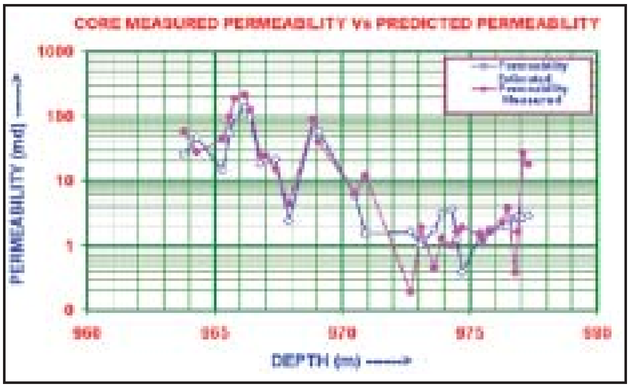


Fig.4 : Core measured/ estimated perm; Well- P1A-1.

Mathematical testing of very good results obtained through at-a-glance view of the data sets approach suggested here using ACE is essential prior to using it for generating the permeability profiles for all the wells of L-II reservoir of Mumbai high. For this a plot between the core permeability measured and core permeability predicted for well P1A-1 is shown in figure-5.

Figure-5 indicates co-relation coefficient value is 89%. This value of co-relation coefficient expects very good estimates for the permeability values. To show practical utility of the permeability values estimated through at-a-glance view of the data sets approach described here using ACE out of many few examples are given here.

Figure-6 as first example for utility shows the integrated at-a-glance view of various data sets to see degree of match between measured and ACE estimated k-values using the approach for complete L-II reservoir interval with the available details from the history of the well P2B-1 collected at different points of time. At present this well is completed in L-II reservoir as injector but water injection is closed.

Due to presence of low permeability zones injected

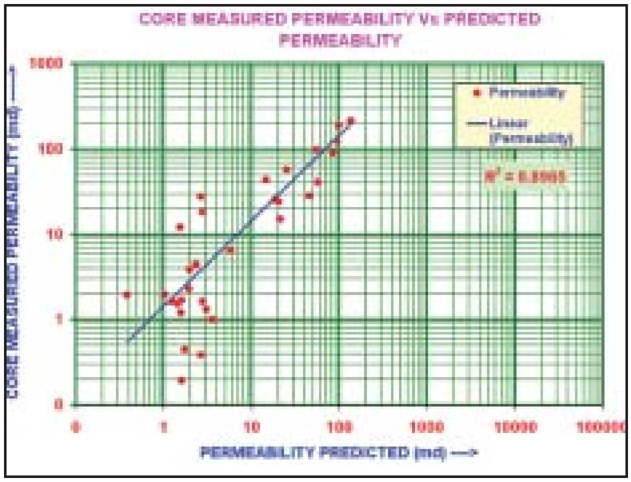


Fig. 5: Core measured/ estimated perm. cross plot ; Well-P1A-1

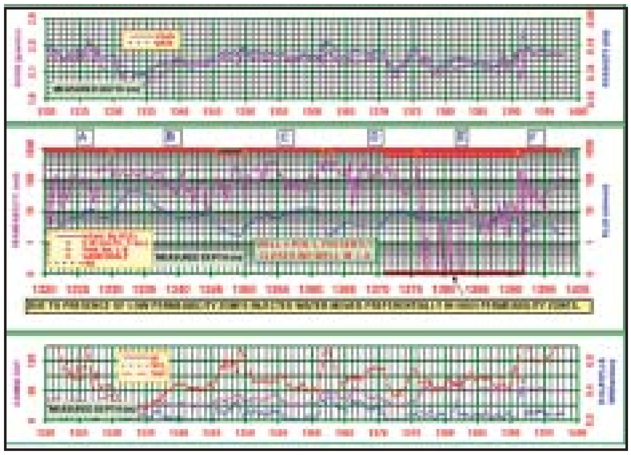


Fig. 6: At-a-glance view of various data sets; Well-P2B-1

water moved preferentially in relatively high permeability zones and flooded the nearby producer for example D zone of well P1A-2 that time (when it was completed in L-II reservoir), where also relatively high permeability is estimated. Presently this well P1A-2 is completed in L-III reservoir (below the L-II reservoir) and producing oil. This indicates injectors can also be treated. Due to preferential movement one zone is flooded but at the same time other zones are deprived of pressure maintenance. So injection / production profiles need optimization.

Figure-7 as second example for utility shows the integrated at-a-glance view of various data sets to see the degree of match between measured and ACE estimated k-values using the approach for complete L-II reservoir interval with the available details from the history of the well P4D-1 collected at different points of time. At present this well is completed in L-II reservoir as oil producer.

Permeability profile indicates interval 1155-60m

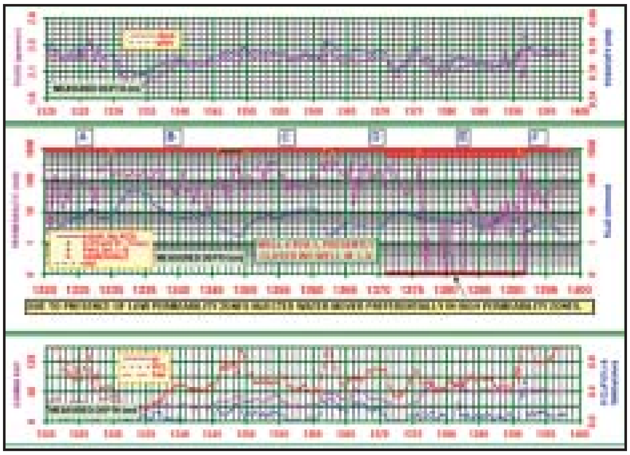


Fig. 7 : At-a-glance view of various data sets; Well- P4D-1

is having good permeability. All the other data set support this view. However PLT data indicates it is not contributing. So interval 1155-58 m must be re-perforated. Partial perforation is suggested to avoid water production from nearby high water saturation layer. This will improve the oil production from this well. So the generated profiles can be used for increasing the oil production from the wells.

Conclusions

In spite of some minor discrepancies, the general agreement between permeability values estimated by the ACE and measured k-values for well P1A-1, does indicate that using this integrated at-a-glance view approach ACE has satisfactorily generalized the relationship between permeability and well logs. The k- values obtained are also comparable to the k-values derived from well test analysis.

Using this integrated approach, continuous ACE derived permeability curves provide detailed vertical variations in important reservoir intervals of the individual wells. These curves allow evaluation of reservoir quality and distribution, and facilitate detailed examination of vertical variations of permeable and less permeable units. The heterogeneity reflected in the predicted permeability curve is of the same order of resolution as the well logs.

Thus generated continuous permeability curves for individual wells have been examined to provide valuable information useful in the context of profile modification, water shut-off, reinterpretation of well test data and work-over jobs. Further the predicted k-values can be utilized in simulation studies for more realistic performance prediction. Remedial measures inferred will not only help in increasing the oil production but also provide better reservoir management and better knowledge of internal structures of reservoir. So it is quite an useful approach.

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Views expressed in this paper are that of the author(s) only and may not necessarily be of ONGC.

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