Enhanced Iterative Formation Evaluation of El Tordillo Field, San Jorge Basin, Argentina: Using Electrofacies and Production Prediction Index Determination

L.P. Stinco, Tecpetrol S.A., and **R.Y. Elphick**, SPE and **W.R. Moore**, SPE, Schlumberger Holditch-Reservoir Technologies

Summary

Formation evaluation, electrofacies, and production prediction index determination based on inductive and deductive methodologies were completed in El Tordillo field, north flank of the San Jorge basin, Argentina. The applied methodology consisted of a number of steps, including the following: editing and normalization of the log data; modeling of the deep resistivity; electrofacies determination; standard log analysis; computing a production prediction index; and summations. Using cutting and core data, the 15 electrofacies determined were associated with the geological facies encountered within the field and on the rock types. Consequently, porosity/permeability relationships were established between the core data and the productive electrofacies. These relationships permit computing permeability from the computed effective porosity. A production prediction index was derived from the computed results and correlated well with existing production data. Zones of possible bypassed production were identified, and some tested successfully. Finally, summations were used as input for original-oil-in-place estimation, geological modeling, and numerical simulation.

Introduction

El Tordillo field is situated on the north flank of the San Jorge basin in Chubut Province, Argentina. It is approximately 50 km from the town of Comodoro Rivadavia and 1500 km south of Buenos Aires (**Fig. 1**). The field was discovered in 1932 and was operated by Yacimientos Petrolíferos Fiscales (YPF) from 1932 to 1991, when the Consortium El Tordillo (in which Tecpetrol S.A. is the operator) assumed operations. More than 1,000 wells have been drilled in the field, and production is spread over approximately 57 km^2.

Hydrocarbons in El Tordillo field are structurally and stratigraphically trapped in numerous fluvial sand bodies that are grouped in three Cretaceous units. These formations are El Trebol, Comodoro Rivadavia, and Mina El Carmen. The latter two formations are analyzed in this work.

The fluvial reservoir units are sandstones with high lithic and pyroclastic (tuffaceous material) content. The quality of the reservoirs generally improves up-section as pyroclastic content decreases, but hydrocarbon accumulations throughout the producing interval are highly compartmentalized because of faulting and the discontinuous nature of fluvial sandstone reservoirs. Refs. 1 and 2 provide relevant geological, geophysical, and engineering observations from studies performed within the field.

In 24 wells located in the southwest part of the field, formation evaluation and electrofacies determination were performed by applying an appropriate set of inductive and deductive methodologies. The analysis was performed over the main producing intervals within the Comodoro Rivadavia and Mina El Carmen formations. The methodology was composed of a number of procedures, including data editing and normalization of the log data, modeling of the deep resistivity, electrofacies determination, standard log analysis, computing a production prediction index, and summations. The analysis procedures were calibrated with the help of cutting descriptions, cores, and production test data. The deep resistivity modeling greatly improved the tool response in thin bed layers and enhanced the quality of the readings. The Dual Water saturation estimation was optimized with the modeled resistivity and the electrofacies control. K-means cluster analysis in four dimensions was used to define 15 electrofacies. The 15 electrofacies were associated with geological facies and rock types using cutting and core data, as well as production data. A good match of the electrofacies data with the geological data was obtained with the remaining data. The consistency of the electrofacies and the computed results was used as a quality control to check the validity of the model parameters through the iterations to the final solution. Porosity/permeability relationships were determined from core data for each of the productive electrofacies. These relationships were used to compute permeability for all depths in all wells from the computed effective porosity and the electrofacies. The results of all the analyses were combined to derive a production prediction index. This index correlated well with existing production data and indicated a number of zones of possible bypassed production; some of these tested successfully. Summations on the results were used as input for original-oil-in-place estimation, geological modeling, and numerical simulation.

Petrophysical Analyses and Methodologies

The petrophysical data processing and analysis was performed following a number of interrelated procedures that were highly dependent on the quantity and quality of the data.

El Tordillo was discovered in the 1930s. The wireline data have been acquired from the initial discovery until the present time. The data, therefore, vary from the old electrical survey (ES) logs that have only spontaneous potential (SP), long normal (LN), and short normal (SN) resistivity—sometimes with the addition of micronormal (MNOR) and microinverse (MINV) curves—to modern suites of logs that have many curves. The wells in the study area were drilled recently enough that all of them have induction and sonic logs; in addition, some have neutrons and densities.

The petrophysical data were treated with deductive and inductive methods to get the most from both approaches. Deductive methods comprise those methodologies that seek to differentiate the data by the computation of a set of component proportions, the identification of which was linked with wireline log data by some suite of response equations.[3] The model was built considering the number of components and the number of variables (data curves). Normally, measures to detect mismatches and gross errors are included in the techniques, although mathematical consistency is not a guarantee of geological accuracy. This situation was well

This paper (SPE 79959) was revised for publication from paper SPE 69479, first presented at the 2001 SPE Latin American and Caribbean Petroleum Engineering Conference, Buenos Aires, 25–28 March. Original manuscript received for review 23 April 2001. Revised manuscript received 6 March 2002. Paper peer approved 3 August 2002.

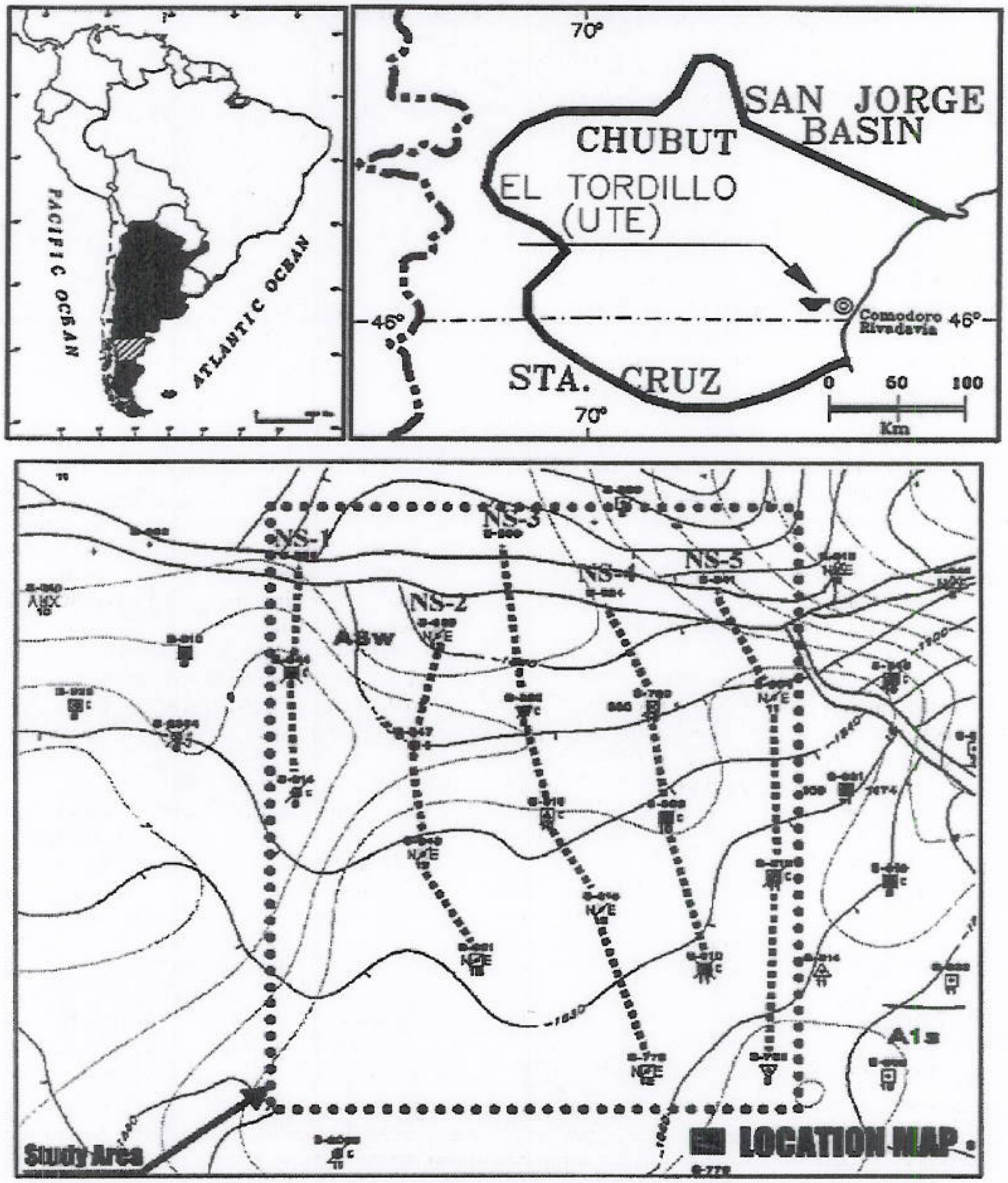

Fig. 1—Location map of the El Tordillo field and the study area.

represented by standard deterministic log analysis. However, inductive methods establish their classes or transformations based on the data set and do not depend on any predetermined correlation among the components. These methods tend to isolate distinctive patterns and to derive classifications or new variables that can be interpreted with a physical meaning. Cluster analysis is an example of this type of methodology.

Editing and Normalization of the Log Data. As usual, the preprocessing of the wireline data was vital to their reliable interpretation. The subtasks, performed with standard techniques and standard computer programs, included the following:

- Edited the digital wireline log data, including resampling to a common increment where necessary.
- Compared the digital data with the paper logs and repaired where differences occurred.
- Concatenated logging runs, choosing the best data from any overlaps or repeat sections.
- Performed standard editing to remove obvious data errors or spikes.
- Performed depth shifting for each logging suite to the resistivity suite.
- Performed final editing and removed SP drift.
- Performed resistivity modeling to better resolve thin bed resistivities.
- Performed environmental corrections.
- Depth shifted all core data to logs and added to database.
- Plotted crossplots and histograms of all curves.
- Normalized all curves with the crossplots and histograms.

Because crossplots provided two dimensions and, therefore, could display and differentiate rock groupings in a way that 1D histograms could not, they were preferentially used wherever possible.

Experience in using well-log analysis within integrated reservoir studies has shown repeatedly that multiwell normalization is necessary to ensure that results are accurate, consistent, and comparative well-to-well. Once normalized, the wireline log data were effectively integrated, correlated, and calibrated with core data. Consequently, correlations were extended vertically to include layers that were not cored and laterally to wells across the study area.[4]

The normalization used a statistical approach because of the lack of known formations with fixed properties that could be used to calibrate the procedure. Because no homogeneous layer could be used to calibrate the wells, the curves were normalized to the average readings on the hypothesis that, on average, the field calibrations are correct. Consequently, the assumption was confirmed to be valid because the computed properties derived from the openhole logs match with core and test results. **Figs. 2 and 3** show examples from the normalization process.

Modeling of the Deep Resistivity. Resistivity measurements are strongly influenced by:

- Borehole volume/drilling-fluid conductivity.
- Borehole washouts.
- Filtrate invasion.
- Vertical resolution problems (bed shoulder and thin bed effects).
- Dipping beds.

These problems with resistivity measurements have long been known and understood. Various semiquantitative methods for dealing with the problem have been developed, most of them being "rules of thumb" that have had some value in localized applications. Around 1990, some creative early attempts at forward modeling and inversion processing were developed; very good solutions could be achieved with some of these methods. However, long processing times on expensive workstations prevented even the most skilled log analysts from effectively taking advantage of the new technology. More recently, the availability of inexpensive, high-speed PC hardware and high-speed processing software has transformed these techniques into practical solutions for large projects with multiwell applications.

Resistivity modeling applies forward modeling and inversion processing and determines true formation resistivity (R_t) with a much more accurate resolution of bed boundaries.[5] Where thin beds predominate among low-resistivity beds (such as shales), the resistivity tools do not read the correct values of the thin beds because of the attenuation caused by the surrounding beds. This problem often occurs in fluvial and turbidite depositional systems. Resistivity modeling can compensate for the effects of the surrounding beds and calculate a resistivity that is much closer to the true resistivity of the thin beds **(Fig. 4).**

In this particular case, a direct comparison of the water saturation computed with and without the modeled resistivity showed an increase of more than 30% in the oil saturation of the thin beds. In other cases, different results may be obtained.

Electrofacies Determination. The term electrofacies was used originally to describe a set of log responses that characterized a bed and permitted it to be distinguished from others.[6] They are determined at least in part by geology because wireline log responses are measurements of the physical properties of rocks and the fluids that they contain. There is a conceptual difference between geological facies—related in their genesis—and the electrofacies[7] that are primarily observational in origin. Therefore, electrofacies constitute a set of technologies used to recognize rock types with common properties. Typically, these electrofacies are used to provide assistance in performing sequence stratigraphy and correlations. In addition, they can be used to assign relationships for each rock type, such as porosity/permeability equations.

There are two main approaches to electrofacies. The first is a deterministic approach, in which facies determined from core description work are forced onto a suite of logs.[8] The second is a cluster analysis approach, in which the clustering techniques determine which rock types the log suites are sensitive to.[9] In either case, porosity/permeability relationships for the rock types may be determined and used to calculate improved permeabilities from the wireline logs. The cluster analysis approach was used in this study. Electrofacies also can be very valuable in identifying geological facies and can be of assistance in sequence stratigraphy interpretations of the reservoir formations. The technique can be made to be sensitive to the facies associated with major stratigraphic surfaces (such as flooding and erosional surfaces), particularly when curves sensitive to fluid content (such as resistivity curves) are used.

The electrofacies interpretation workflow used for this study is summarized in the following list:

- Studied all core data for the 24 study wells.
- Studied drill-cutting data for calibration wells.
- Depth matched the core data to the wireline logs (mostly with porosity).
- Performed cluster analysis for both data sets.
- Compared electrofacies with geological data and fine-tuned.
- Performed electrofacies analysis on all remaining wells.
- Compared the results with geological data.

Cluster Analysis. Cluster analysis is probably the most common and longest-established multivariate technique in use on petrophysical data.[3] It is supported by the theoretical concept that a given set of data can be clustered into groups that differ from each other in meaningful ways. This principle is normally true at any scale of investigation given the appropriate geological framework within which all petrophysical analyses are undertaken.

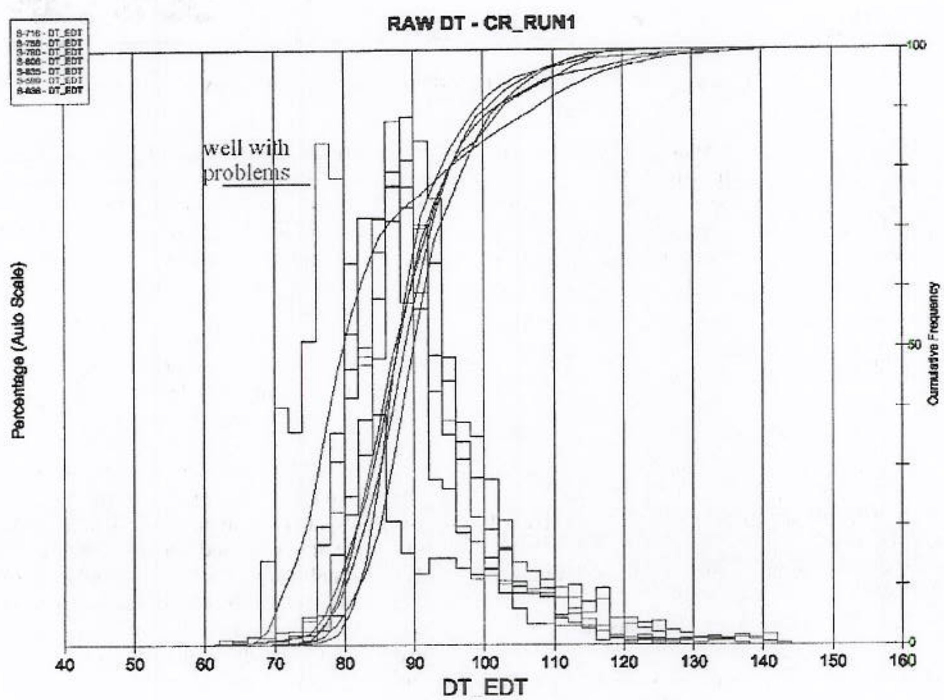

Fig. 2—Sonic log data before the normalization process.

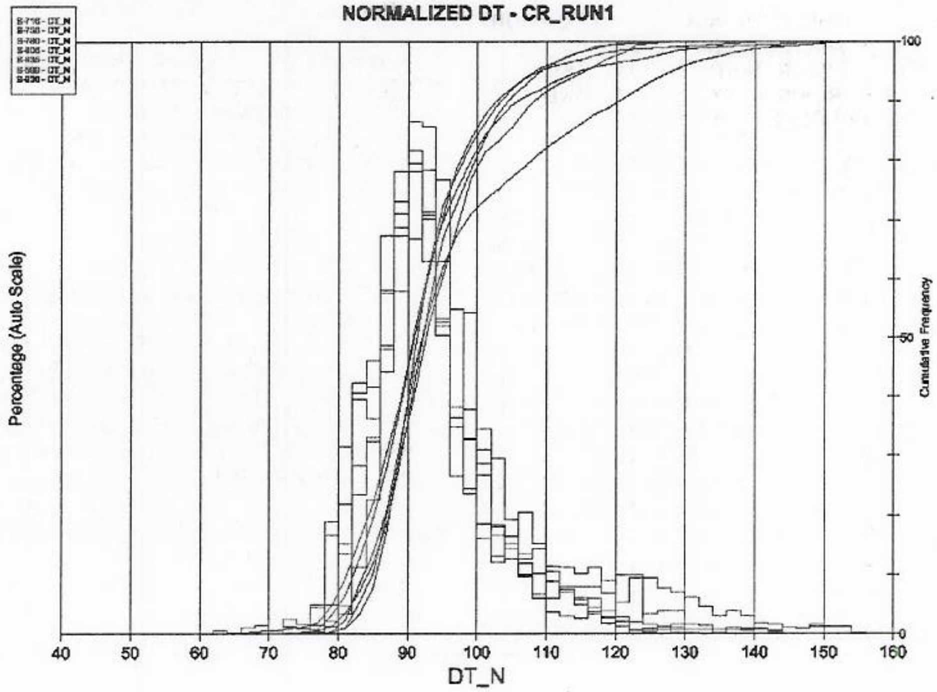

Fig. 3—Sonic log data after the normalization process.

There are four main types of algorithms for clustering:[10] partitioning methods, K-means, mutual similarity, and hierarchical clustering.

El Tordillo electrofacies determination was performed with K-means cluster analysis. The K-means approach is a special case of a general approach called the expectation and maximization (EM) algorithm.[11] Given a specific number of clusters, this method is practical for much bigger data sets than any other algorithm. This approach iteratively alternates between cluster assignment and re-estimating cluster centers. The user chooses the number of clusters to find. The system then populates the n dimensions (four, in this case) with the same number of points approximately evenly spaced throughout the data. The iterative steps then move the points toward the data populations (like gravitational attraction) until no more movement occurs. The final positions of the points are then taken to be the central positions of the clusters in the data.

At first, several different numbers of clusters were tried (18 clusters, 15 clusters, 12 clusters, and 10 clusters) against the chosen log curves. After several iterations, 15 clusters was preferred as being an appropriate number that resolved the essential sandstones, as well as the other important facies (**Table 1**).

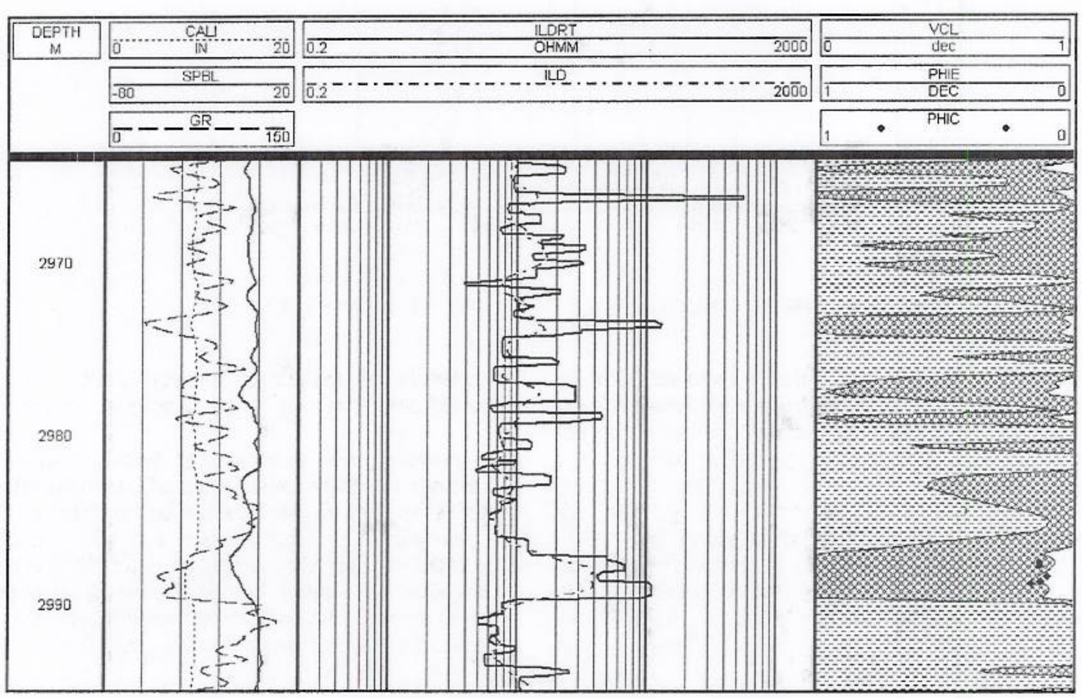

Fig. 4—Comparison between the raw (ILD) and modeled (ILDRT) resistivity in Track 3. The figure also shows the good matching between the core and computed porosities in Track 4.

TABLE 1—CLUSTER DETERMINATION ACCORDING TO FOUR DIMENSIONS AND FOUR WIRELINE LOGS: SONIC (DT_N), LOGARITHM OF SHALLOW RESISTIVITY [LOG(RS)], LOGARITHM OF DEEP RESISTIVITY [LOG(RT)], AND SPONTANEOUS POTENTIAL (SP_N)*					
Cluster	Count	DT_N	Log(RS)	Log(RT)	SP_N
1	307	64.25	1.99	2.04	−18.50
2	178	65.32	1.83	1.94	−42.47
3	2,721	72.91	0.84	0.83	−13.89
4	718	65.09	1.41	1.42	−15.33
5	522	69.25	1.38	1.44	−27.79
6	762	99.11	0.25	0.41	−11.66
7	1,983	69.32	1.07	1.06	−15.52
8	364	69.97	1.33	1.39	−48.52
9	1,440	86.20	0.43	0.50	−11.53
10	95	61.48	2.81	2.83	−17.76
11	382	116.97	0.18	0.36	−11.26
12	2,283	78.83	0.65	0.66	−12.35
13	262	69.32	1.37	1.39	−67.68
14	500	74.07	0.93	0.97	−28.90
15	678	80.15	0.68	0.72	−21.87

*N = normalized data.

The number of wireline logs (*n* dimensions) finally used was reduced to the most essential common logs run in all the wells: deep resistivity, shallow resistivity, sonic (compressional wave), and spontaneous potential **(Fig. 5).** This was done for several reasons:

• The resistivity curves generally provided more useful clusters when rock types with fluid characteristics were important.

• The quality of the porosity logs was affected by the prevalent washed-out zones.

• The electrofacies technique was much more effective when applied to all the wells (the four chosen curves were available for all the study area wells).

The number of clusters was varied, and the results were compared with geological data (drill-cutting descriptions, core descriptions, and thin sections) and production data until an optimal set of electrofacies was found for the two calibration wells. The optimal set chosen contained 15 electrofacies from 15 clusters. These electrofacies were able to represent the variety of geological facies that comprise both the reservoir units and the impermeable layers. Moreover, vertical and horizontal distributions of electrofacies within the stratigraphic column proved to have geological correlation with the successive depositional environments recognized throughout the geological history of the area.

Standard Log Analysis. Because of the ranges of vintages of the logs within the field study, a systematic methodology was chosen that could interpret all types of logs appropriately. The modern logs were interpreted first with the industry-accepted techniques described later. Then, all the wells were interpreted with the sonic while taking advantage of the experience and knowledge gained during the interpretation of the newer logs with neutron and density curves. The programs used to interpret the wireline logs were written especially for this study and developed as the study progressed. The parameters used for the analysis were chosen for four zones representing the most relevant lithological changes within the sedimentary column.

The programs were written to make four separate calculations:
• Shale and lithology.
• Total and effective porosity.
• Fluid saturation.
• Permeability.

The volumes of shale, volcanic material, and sand were determined from the SP and the resistivity. The algorithms and parameters used for the computation were chosen with the help of sam-

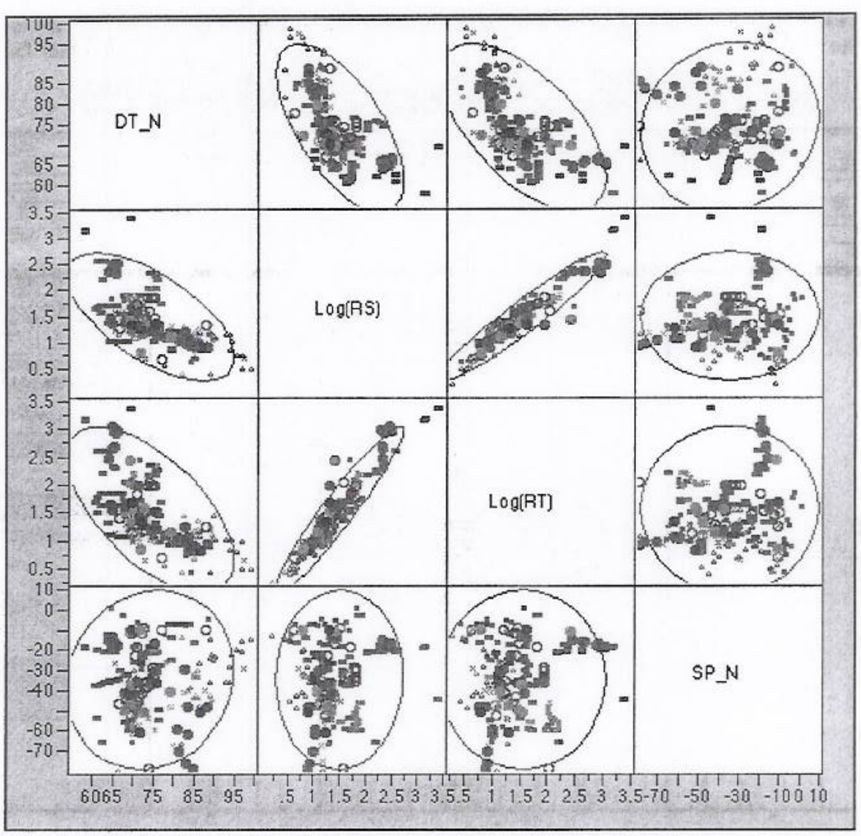

Fig. 5—Population of facies against log data.

ple descriptions, core descriptions, and the output of the calibrated electrofacies.

The total porosity was determined from the sonic logs because these curves were available for all the wells in the study. In seven wells, where the three porosity logs were registered, the sonic response was calibrated from the neutron and density logs. This procedure was done independently for each of the four zones. The effective porosity (PHIE) was calculated from the total porosity by applying a correction proportional to the shale content.

As part of this project, two water saturation (S_w) techniques were compared on a test well. The techniques tested were Archie[12] and Dual Water.[13] After discussing the results, the authors agreed that the Dual Water method provided more stable results, especially in the lower-porosity zones. Water salinity values, taken from measurements of produced water samples, ranged from 18,000 ppm for the Comodoro Rivadavia formation down to 6,000 ppm for the Mina El Carmen Formation. This variation in water salinities is natural (commonly encountered within the producing units of the San Jorge Basin) and agrees with mineralogical changes throughout the stratigraphic column. Geological correlation of the reservoir units provided the water salinity values to be used when no production data were available. The cementation exponent taken from standard core analyses was between 1.85 and 2.05, while the saturation factor was taken to be 2.0.

The permeabilities (PERM) were determined from the calculated effective porosity (PHIE) and adjusted with three factors related to the slope and offset of the porosity/permeability relationship (PERMS, PERMO) and the electrofacies (PERME). The relationship took into account the positive or negative influence of each electrofacies in the permeability as follows: $\mathrm{PERM} = 10^{(100*\mathrm{PHIE}*\mathrm{PERMS}+\mathrm{PERMO}-\mathrm{PERME})}$.

Table 2 summarizes the most important computed parameters derived from the standard log analysis.

The log analysis was performed in a series of iterations. After each iteration, summations of each of the test intervals were compared with the production and test results. In addition, the lithologies and porosities were compared to the electrofacies, core data, and sample descriptions. At each iteration, the equations and parameters used were adjusted to provide improved agreement of the log analyses with all other data.

Production Prediction Index. Initial predictions of production made from log analyses depended loosely on the following:

- Porosity greater than 10% (preferably greater than 12%).
- Water saturation lower than 70% and irreducible (or a constant bulk water volume), preferably water saturation lower than 55%.
- Permeability greater than 10 md.

These parameters were chosen to provide the greatest agreement with the production data during the previously mentioned iterations and were fine-tuned at that time. In addition, the general shapes of the curves also were taken into account so that changes in grain size and possible water contacts were included.

Once the verification had been completed, an improved predictor of potentially productive zones was devised. This process was done in several steps. The first step was to calculate the average oil specific gravity for a zone that was derived from the average of produced oil values from each zone. Common oil specific gravity values for the Comodoro Rivadavia formation are within the range 0.900 to 0.925, down to 0.825 for Mina El Carmen formation producing units. Second, viscosity (μ) was computed and adjusted according to the average oil specific gravity for a zone and its temperature, applying a Beal's correlation type approach. Finally, a new variable ($k\mu$) was derived from the product of the electrofacies dependent permeability (PERM) and the viscosity (μ). $k\mu$ ponders simultaneously the impact of the quality of the reservoir at a very detailed level (electrofacies) and the resistance of the fluid to movement.

Assigning a convenient range of values to the estimated effective porosity, water saturation, and $k\mu$ (see **Table 3**), potentially productive zones could be identified by calculating a total score. Where the total score was greater than 5, the zone was probably oil productive (though with a possible water cut). Higher values of the score increased the probability of water-free oil production. This curve is presented on the final log plots and is shaded for values greater than 5 **(Fig. 6)**.

Fig. 7 shows a comparison of the production prediction index and the test results in the analyzed wells. The index was able to discriminate zones with oil production from intervals with water with a success of 70%. Additionally, an interesting conclusion arose from the analysis of the tight or no-flow zones with the index and the computed permeability. In the majority of the cases, an important formation damage was detected that justified the disagreement between the index and the test result.

Results

Summations on 116 sands within the Comodoro Rivadavia formation and 92 sands in Mina El Carmen were performed for the 24 analyzed wells.

The data were used as input for original-oil-in-place estimation, geological modeling, and simulation. Moreover, these results were used for characterizing the most important reservoir units, and property maps were generated for the petrophysical variables **(Fig. 8)**. **Fig. 9** shows the modeled facies distribution along the north/south cross section 1 (NS-1 from Fig. 1).

With the help of the production prediction index, 15 intervals in nine different wells were found. Only three of the horizons were tested; those cases all tested successfully.

Conclusions

1. Formation evaluation, electrofacies, and production prediction index determination based on inductive and deduc-

TABLE 2—SUMMARY OF THE MOST IMPORTANT COMPUTED PARAMETERS DERIVED FROM LOG ANALYSIS

Comodoro Rivadavia Formation			
Parameter	Maximum	Average	Minimum
Net Reservoir (m)	10	3	0.5
Effective Porosity (%)	30	15	7
Water Saturation (%)	90	45	26
Average Computed Permeability (md)	3,000	50	1
Mina El Carmen Formation			
Parameter	Maximum	Average	Minimum
Net Reservoir (m)	13.6	2.5	0.5
Effective Porosity (%)	22	12	7
Water Saturation (%)	90	60	12
Average Computed Permeability (md)	1,050	30	2

TABLE 3—COMPUTED PARAMETERS AND CONDITION SCORE

S_w <= 40%	5
40% < S_w <= 60%	4
60% < S_w <= 80%	3
80% < S_w	0
PHIE >= 15%	2
15% >PHIE >= 10%	1
10% >PHIE	0
$k\mu$ >= 10.0	2
10 > $k\mu$ >= 1.0	1
1.0 > $k\mu$	0

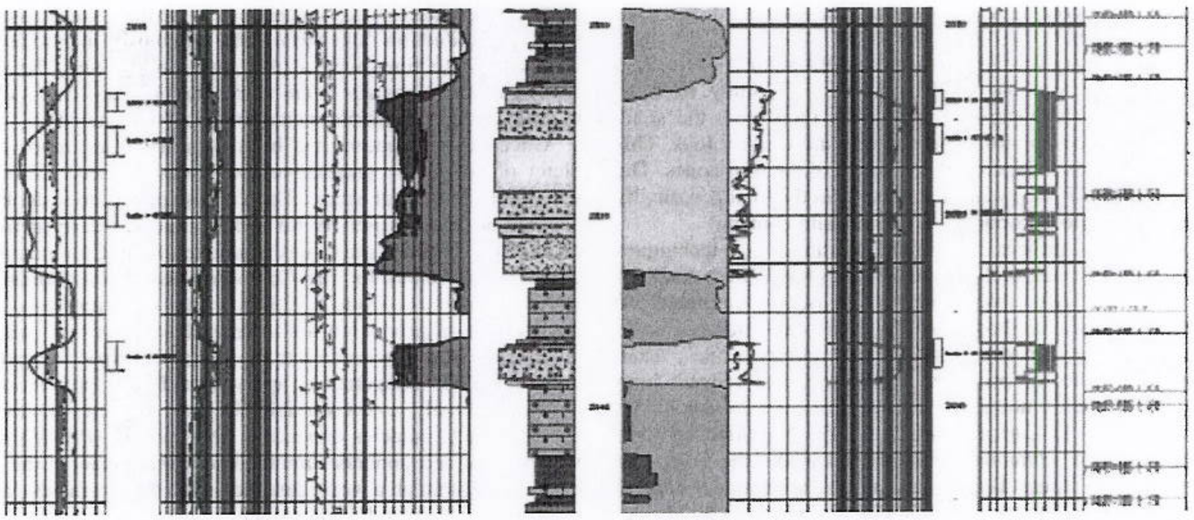

Fig. 6—Petrophysical evaluation, electrofacies, and production prediction index determination in Well S-848. Track 1 contains the SP and caliper. Track 2 is a depth track with tested intervals. Track 3 shows the resistivities. Track 4 represents the porosity tools (sonic). Track 5 shows the effective porosity and bulk water volume. Track 6 contains the calculated electrofacies. Track 7 shows the lithological analysis from logs. Track 8 shows the calculated water saturations. Track 9 shows the computed permeability. Track 10 is a depth track. Track 11 shows the production prediction index (shaded where production is probable). Track 12 contains the zone tops.

tive methodologies proved to be very useful when analyzing highly heterogeneous clastic sediments, such as the ones represented by the Comodoro Rivadavia and Mina El Carmen formations.

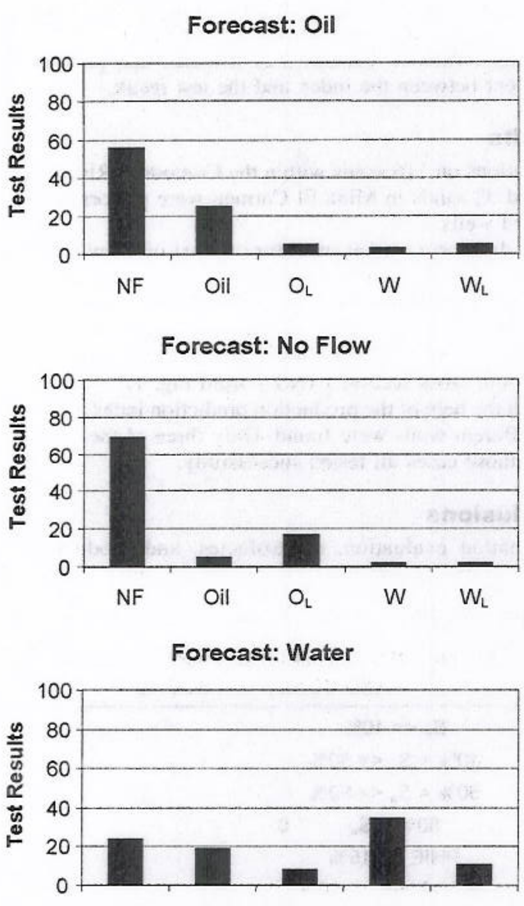

Fig. 7—Comparison of the production prediction index against test results. NF= no flow; Oil= production of oil; O_L= low production of oil; W= production of water; and W_L= low production of water.

2. An increase of more than 30% in the oil saturation of the thin beds was gained through resistivity modeling.
3. Using a minimum of log data (spontaneous potential, deep resistivity, shallow resistivity, and sonic), 15 electrofacies were determined that provided good agreement with the geological facies.
4. Electrofacies determination helped in defining a valid porosity/permeability relationship, calibrating the standard log analysis, estimating fluid saturation and permeability, and computing the production prediction index.
5. The production prediction index was able to identify possible zones of bypassed production.
6. Summations provided the necessary data for the oil-in-place estimation, geological modeling, and reservoir simulation.

Nomenclature

k = permeability, md
R_t = true formation resistivity, ohm.m
S_w = water saturation, percent
μ = viscosity, cp

Acknowledgments

The authors wish to thank Tecpetrol S.A., Consortium El Tordillo, and Schlumberger Holditch-Reservoir Technologies for permission to publish this paper.

References

1. Muruaga, E. *et al*: "Integrated Reservoir Study in El Tordillo Field," paper SPE 69688 presented at the 2001 SPE Latin American and Caribbean Petroleum Engineering Conference, Buenos Aires, 25–28 March.
2. Taboada, R. *et al.*: "Tordillo Reservoir Static Characterization Study: El Tordillo Field, Argentina," paper SPE 69660 presented at the 2001 SPE Latin American and Caribbean Petroleum Engineering Conference, Buenos Aires, 25–28 March.
3. Moss, B.: "The partitioning of petrophysical data: a review," in *Developments in Petrophysics,* Geological Society Special Publication No. 122, M. Lovell and P. Harvey (eds.), The Geological Society, London (1997).
4. Hunt, E. *et al.*: "Fundamentals of log analysis. Part IV: Normalizing logs with histograms," *World Oil* (October 1996) 101.
5. Petroleum Software Technologies LLC: *PST-Mod Manual,* Denver (2000) 94.

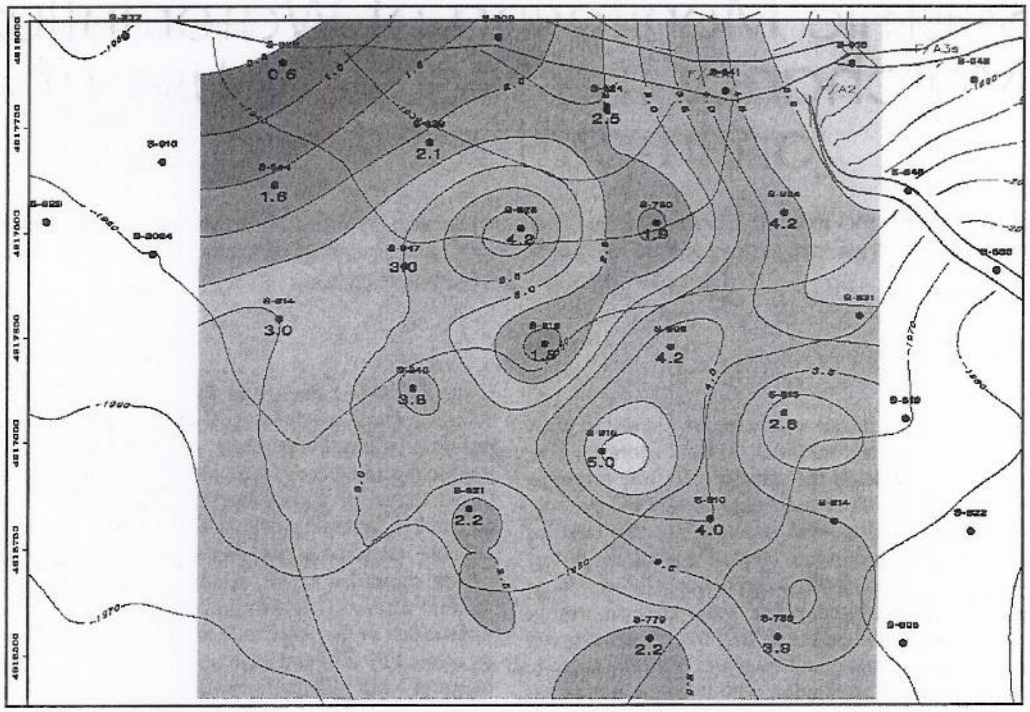

Fig. 8—Net reservoir map based on petrophysical data.

6. Serra, O. and Abbott, H.T.: "The Contribution of Logging Data to Sedimentology and Stratigraphy," *SPEJ* (February 1982) 117.
7. Doveton, J.: *Geologic Log Analysis Using Computer Methods,* AAPG Computer Applications in Geology, No. 2, AAPG, Tulsa (1994) 170.
8. Elphick, R.Y. *et al.:* "A deterministic method for calculating facies from wireline logs," *The Log Analyst* (1996) **37,** No. 2, 14.
9. Elphick, R. and Moore, R.: "Permeability Calculations from Clustered Electrofacies, A Case Study in Lake Maracaibo, Venezuela," paper presented at the 1999 SPWLA Annual Symposium, Oslo, 30 May–3 June.
10. Davis, J.: *Statistics and Data Analysis in Geology,* second edition, Wiley, New York City (1986) 605.
11. SAS Institute Inc.: *JMP Statistical Discovery Software. Statistics and Graphics Guide,* Cary, North Carolina (2000) 634.
12. Archie, G.: "Electrical Resistivity Log as an Aid in Determining Some Reservoir Characteristics," *Trans.,* AIME (1942) **146,** 54.
13. Clavier, C., Coates, G., and Dumanoir, J.: "The Theoretical and Experimental Bases for the 'Dual Water' Model for the Interpretation of Shaly Sands," paper SPE 6859 presented at the 1977 SPE Annual Technical Conference and Exhibition, Denver, 9–12 October.

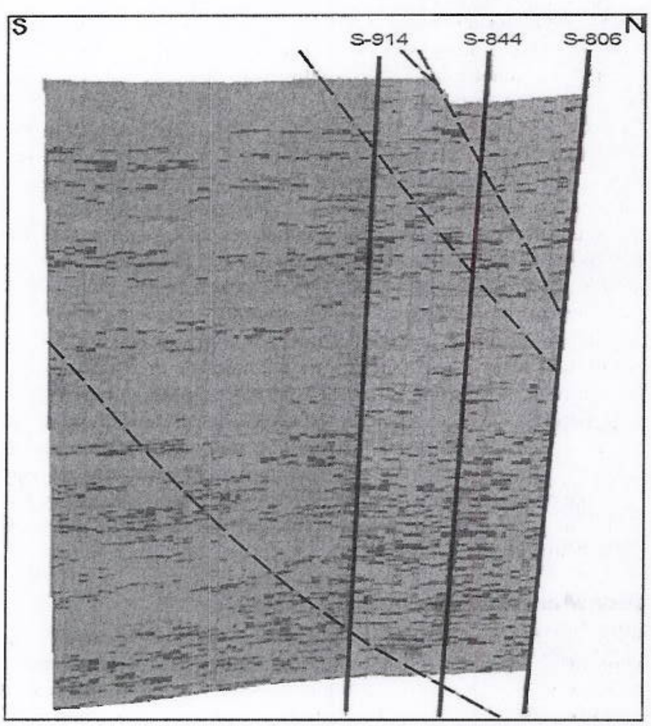

Fig. 9—Facies distribution along the NS-1 cross section.

SI Metric Conversion Factors

ft × 3.048*	E–01 = m
mile × 1.609 344*	E+00 = km

*Conversion factor is exact.

Luis P. Stinco worked for the Antarctic Inst. of Argentina before joining the oil industry in 1987. After working for Exploration Logging, Western Atlas, Shell, and CGC, he joined Tecpetrol in 2000. He is focused on petrophysics, reservoir characterization, and formation evaluation. Stinco has taught log-analysis courses for universities and industry since 1990 and is the author of several papers. He holds an MS degree in geology from the U. of Buenos Aires. **Robert Y. Elphick** joined the oil industry in 1975 as a field engineer with Schlumberger in Louisiana. Since 1980, he has worked in petrophysics and reservoir characterization for Canadian Superior, Sohio Petroleum, Occidental Petroleum, and Scientific Software-Intercomp, and he most recently joined Schlumberger H-RT. He holds a BS degree in applied physics from the U. of Central Lancashire (Harris College) and an MS degree in geophysics and planetary physics from the U. of Newcastle. **W.R. Moore** joined the oil industry in 1977 as a mud logger with The Analysts in Houston. From 1981 to 1988, he worked for Exxon Co., U.S.A. in Denver as a wellsite, operations, and project geologist. From 1988 to 1998, he worked as a petrophysical consultant out of Denver; he joined Schlumberger H-RT in 1998 as a geoscientist. Moore holds a BS degree in geology from Campbell College.