A COHERENT FRAMEWORK FOR DEVELOPING AND APPLYING MULTIPLE FORMATION EVALUATION MODELS

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ABSTRACT

Quantitative evaluation of logs requires a formation model. The formation evaluation model comprises the constituents of the formation, the tool responses to these constituents, and physical constraints.

Simple log analysis programs assume the same model throughout the interval to be interpreted. Vaguely defined parameters and 'cosmetics' are often used in place of an explicit definition of the model. More advanced programs use solution methods which invert a model in a consistent way. However, the model selection has to be done manually and is usually based on a visual inspection of results. No aids are provided for the selection and combination of models.

A new technique is presented in which several models may be computed and examined simultaneously. Individual models are then assigned a probability in each formation or electrofacies. Results are calculated by automatically selecting or combining models according to their probability. In order to make full use of this capability a consistent system of interpretation and software tools is provided to help the analyst develop and test models.

INTRODUCTION

Log analysis is one example of a geophysical inverse problem. To predict the response of a sensor from a known physical system is called a forward problem. Classical level-by-level log analysis in which we find the physical properties of a formation from sensor measurements is called an inverse problem. The log analysis problem is:

Given n different log measurements, what are the quantities of the m different mineral and fluid volume fraction components which comprise the formation at each level?

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This is the inverse of the forward problem:

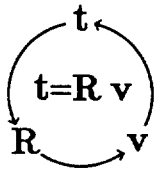
$$\mathbf{t} = \mathbf{R}(\mathbf{v},\mathbf{p})\ \mathbf{v}$$

where $\mathbf{t}$ is the $n \times 1$ vector of log measurements, $\mathbf{R}$ is the $n \times m$ tool response matrix operator of physical parameters, $\mathbf{p}$ is a parameter vector, and $\mathbf{v}$ is the $m \times 1$ vector of unknown component fractional volumes.

In the simplest case (which is practically true for most nuclear logging measurements) $\mathbf{R}$ is simply the matrix of constant response parameters which premultiplies the volume component vector $\mathbf{v}$, itself subject to certain physical constraints. Typically, these constraints are that all fractional volumes must be greater than or equal to zero, and less than or equal to unity. If this is the case the tool response equations can be written as:

$$\mathbf{t} = \mathbf{R}\mathbf{v}$$

In more complicated cases (especially when conductivity responses are used) $\mathbf{R}$ will become a nonlinear matrix operator. Whether or not the inverse problem has a unique solution, there is always an intimate connection between the elements:



To manipulate these relations we require the software system to work three ways:

Find $\mathbf{t}$, given $\mathbf{v}$ and $\mathbf{R}$, *the forward problem.*

Find $\mathbf{v}$, given $\mathbf{t}$ and $\mathbf{R}$, *'classical' log analysis.*

Find $\mathbf{R}$, given $\mathbf{v}$ and $\mathbf{t}$, *the parameter estimation problem*

The system should also aid in finding an appropriate model and determining whether it is well conditioned or badly conditioned. This paper describes features of a computer system that provides a framework for the general numerical solution of tool response equations subject to linear constraints. The user can select either the classical nonlinear tool response functions or an approximation by linear forms. Errors resulting from incorrect parameter selection are in most cases much larger than those caused by linear approximation. Hence, the linear system is adequate for problems of component and model selection.

In this system log analysis is treated explicitly as a petrophysical inverse problem with close links to geology. Formation components are geological quantities with measurable properties. A direct connection is now established between the mineral components of rocks and the associated electrofacies and petrophysical model.

Multiple individual models, each of which corresponds to a particular formation type or petrophysical situation, can be computed in parallel. Either by using *a priori* knowledge or by applying various quantitative criteria based on geological data, the appropriate answer may be selected and displayed. This provides a direct link to geology, and in the process eliminates the need for many 'cosmetics' which are often needed because of incomplete specification of the petrophysical model.

The volumetric mineral framework is extended to fluid components. Saturations and porosities can now be seen as geological variables derived from the basic physical fluid volumes. Such terms as 'effective' and 'total' porosity or saturation become a matter of definition and are open to several interpretations whenever ambiguous components are present.

THE FORWARD PROBLEM

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The first component of the system is a program that solves the forward problem. This program not only provides a means for verifying solutions to inverse problems but also can be used for some other interesting applications. The program is structured to generate synthetic logs and electrofacies data bases[1] from a volumetric description of formations using known tool response equations and parameters. It may also be used to generate synthetic logs from a previously defined electrofacies data base. This allows the analyst to assess the inherent confusion between the database facies as a function of selected tool combinations.

The generation of electrofacies represents an approach for combining local geological knowledge with local petrophysical tool response knowledge to construct a consistent electrofacies data base. Once this is done, multiple electrofacies can readily be associated with mineral models. Then using a statistical pattern recognition approach[1] the probability of each electrofacies, and thus of each mineral model, can be found.

Synthetic or reconstructed logs are calculated by a direct application of the tool response equations to input formation volumes and parameters. For example, the synthetic density log, $\hat{\rho}_b$ is generated by evaluating the equation

$$\hat{\rho}_b = \sum_{i=1}^{n} \rho_i v_i + \epsilon,$$

where the noise parameter ϵ is obtained for each sample by statistically sampling within the range of the tool uncertainty.

Tool response parameters are selected to be consistent with those used in the inverse problem. These response parameters constitute petrophysical knowledge.

For electrofacies computation, an average volume and standard deviation must be input for each component of the rock type to be modeled as an electrofacies. The program then statistically selects a volume for each component from within the allowed range and builds a composite rock response. This sampling is repeated several hundred times in order to get a full sampling of the input volumes. The volumes of the composite rock are then used as inputs to the synthetic log generation described above. The means and covariances of the synthetic logs are computed and output as an electrofacies data base for that specific rock type. The program SYNDAT computes 100 electrofacies for 10 logs with linear or nonlinear responses in approximately 5 minutes CPU time on the VAX 11/780.

Gypsiferous Dolomite	Mean Value	Standard Deviation
WAT	.015	.015
DOL	.685	.120
GYP	.140	.080
ANH	.060	.040
ILL	.050	.040
QUA	.050	.050

Table 1

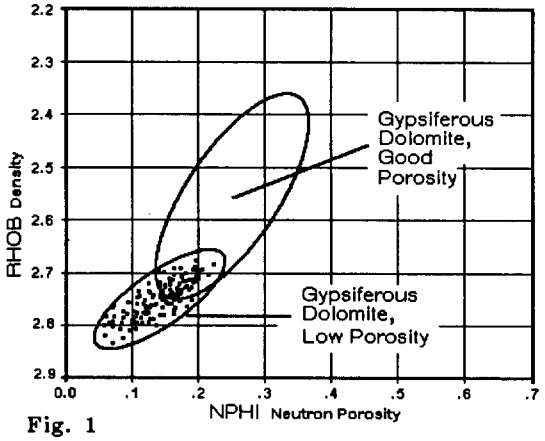

Fig. 1

The essence of this process is depicted above. A volumetric description of a low-porosity gypsiferous dolomite facies is presented in the table. Means and standard deviations are listed for water-filled porosity and the mineral components. The cross-plot shows synthetic log data, generated by statistically sampling from these volumes and applying the response equations. The two-sigma ellipses displayed are automatically computed, displayed, and saved by the program.

THE INVERSE PROBLEM

Inverse methods[2] for solving the classical log analysis problem rely upon iterative generation of the tool vector. Repeated solutions of the forward problem are made which find the variables that minimize the error between the observed and reconstructed responses. Allowances for statistical uncertainties in the parameters, variables, and equations can also be included.

It has been found that by reformulating the standard log analysis response equations in terms of *volumes* of minerals, water, oil, and gas, rather than saturations, most log analysis optimization problems fall into two categories:

(1) Sum of squares of *linear* response functions with *linear* constraints.

(2) Sum of squares of *nonlinear* response functions with *linear* constraints.

Solutions to both these types of problems can be obtained without adjoining the constraints by using penalty constants,[2,3] which are known to deteriorate the numerical characteristics of the problem. The solution of the category (2) problem can be considered an iterative application of the category (1) solution process. The sum of squares problem without constraints can be written as:

$$\texttt{inco} = (\mathbf{Rv} - \mathbf{t})^{\mathrm{T}}\mathbf{D}(\mathbf{Rv} - \mathbf{t}) = (\hat{\mathbf{t}} - \mathbf{t})^{\mathrm{T}}\mathbf{D}(\hat{\mathbf{t}} - \mathbf{t})$$

where $\mathbf{D}$ is the matrix of uncertainty values and ^{T} denotes the vector transpose. The performance function 'inco' measures disagreement between the model reconstructed tool vector $\hat{\mathbf{t}}$ and the observed tool response vector $\mathbf{t}$.

When $\mathbf{R}$ is a constant coefficient matrix, the performance function inco is a quadratic function of the volumetric components and is minimized by setting the vector partial derivative of "inco" with respect to $\mathbf{v}$ equal to zero. The solution, representing the best possible agreement between the model and actual tool data, is readily attainable analytically and is unique.

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The condition number of $\mathbf{R}^{\mathrm{T}}\mathbf{DR}$ is calculated. A large value indicates that the model is ill-conditioned. The condition number also measures the sensitivity of the results $\mathbf{v}$ to small changes in response coefficients in the matrix $\mathbf{R}$.

The 'model' referred to in the above discussion does not include any constraints. Some constraints are physical and must always be included, such as the fact that all volumetric components are nonnegative and must sum to one. Other constraints may be petrophysical and can be obtained from geological, core, or other data. Such constraints are readily definable and accessible to the user. The general format of the linear inequality constraints for this system are of the form:

$$c_1v_1 + c_2v_2 + \cdots + c_nv_n \leq d_1t_1 + d_2t_2 + \cdots + d_{m-1}t_{m-1} + d_m,$$

where v_i are the volumetric components, t_i is the actual observed tool response, and the other parameters are user-defined constants. Examples of the generality of this formalism are shown later.

The addition of the linear inequality constraints does not detract significantly from the minimization process. Minimization of the quadratic incoherence function subject to linear inequality constraints still possesses a unique and readily attainable solution.[3] Such constraints are always satisfied at the solution by the quadratic programming optimization approach which has been used.

The optimization techniques implemented in our current system for the nonlinear sum of squares problem (2) have resulted in a factor of four reduction in computer time from the penalty constant approach.[2] Moreover, linear sum of squares problems (1) are solved using quadratic programming techniques in approximately one-tenth to one-fifth the time of the nonlinear problems, thus making interactive level-by-level computation a practical process.

THE PARAMETER ESTIMATION PROBLEM

The third system component is a program which solves the parameter estimation problem. In this case known tool and volume vectors are available from several levels and the problem is then to solve for a *subset* of the response parameter matrix. It is emphasized that normally only a subset is found since many parameters are known with minimal uncertainty, whereas others are vary widely. For example, the density of quartz is well known, but the sonic response to clays is variable.

To date, the parameter estimation and refinement process[1] has been a tedious, manual process. Our results have shown that when sufficient information is available, parameters are obtained more correctly and expediently by using mathematical optimization techniques.

The parameter estimation problem can also be shown to be a sum of squares optimization problem, subject to linear constraints or bounds on the parameters to be estimated. Thus, the same solution engine used to solve the inverse problem may be applied. The primary implementation problem is the development of a suitable user interface. The current software allows the user to define one or more calibration zones from which user-selected parameters are determined subject to specified parameter bounds. The bounds constitute any *a priori* knowledge about the parameters.

In order to calibrate response parameters for minerals or fluids, the volumes must exhibit sufficient variability. In addition, best results are obtained using the 'fixed parameter rule,' which states that if a response parameter is well known that parameter should be fixed during the optimization. Adherence to these guidelines has resulted in successful solution of the following problem types:

(1) Determination of clay mineral tool response parameters from core data.

(2) Determination of response parameters for new tools.

(3) Ensuring that parameters are consistent between different log measurements.

(4) Detecting incomplete models.

(5) Verification and possible refinement of the environmental correction process.

(6) Calibration of cased hole to openhole logs for the monitoring of floods during secondary and tertiary recovery.

COMPUTER IMPLEMENTATION

Three computer programs provide the general framework described previously. They are incorporated within a software system that also provides data handling, editing, and graphics utilities and runs on VAX/VMS computers. A consistent user interface provides explicit control of models, constraints, and model selection. Arbitrary 'cosmetic' functions, such as 'saturation boosting,' have been totally eliminated. Inputs from any source, such as openhole or cased hole logs, core data, experimental tools, or geological data can be included in formation models.

SYNDAT is a program which solves the forward problem from a comprehensive selection of linear and nonlinear tool response functions. Statistical 'noise' can be applied to create database values for tool responses in any rock type.

The ELAN program is a general-purpose inverse problem solver. It can explicitly define 20 or more mineral components, and it runs several (currently five) models simultaneously. It can be run either interactively on a color terminal or in batch with a user language control file. Parameters, constraints, model selection logic, and display are driven by a menu system.

The CALPAR program solves the parameter estimation problem interactively, given a set of mineral volumes and log responses. These data can come from geological knowledge, core analysis, logs, or other sources. It has an interface similar to that of the ELAN program.

All programs are compatible, with the outputs from one program available for input to another. A data base of some 500 commonly used default values for mineral responses is included.

MODEL COMBINATION

The number of independent component volumes that can be found must always be less than or equal to the number of logging measurements plus one. With the advent of new measurements such as those provided by the Litho-Density*, NGS*, and GST* tools, an increasing number of mineral components can be reliably determined. However in most normal cases the number of *possible* minerals still vastly outnumbers our ability to uniquely invert the logging information. There are various solutions to this problem. One technique is to simplify the model by grouping minerals that occur only in minor quantities with those that predominate and then solving for generic components such as 'limestone,' 'sand,' 'silt,' and 'clay.' This technique allows one to define a model and solve for the predominant minerals in many cases. In some cases shales, shaly sands, carbonates, evaporites, and other rocks exist within a short vertical sequence, and one model is not sufficient, even with a complete logging suite.

The solution presented here is to define several individual models. The analyst defines which mineral and fluid volumes are to exist in each model and the measurements

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that are to be used to determine these volumes. For example, to describe a sequence of individual models for carbonate, evaporite, shaly sand, and shale, the following specification would be made:

Model	Description	Volumes	Input Logs
1	Carbonate	CAL DOL OIL WAT	RHOB NPHI TPL U
2	Evaporite	ANH HAL DOL WAT	RHOB NPHI DT U
3	Shaly Sand	QUA ILL KAO FEL OIL WAT	RHOB NPHI U THOR POTA TPL
4	Shale	QUA ILL WAT	DT NPHI THOR

Table 2

The symbols for the tool and volume components are defined in the glossary.

Next, the individual models are combined to form a single answer. Three methods can be used to combine individual models:

(1) External probability functions can drive the combination of models, as discussed previously in the section on the forward problem.

(2) Assign probabilities based on the volumetric solution for each individual model.

(3) Manually select the model desired.

Manual selection overrides either of the combination schemes based on probabilities. When the analyst elects to combine the models using probabilities, the probabilities for each model are computed so that they are positive and sum to unity. Volumes for the combined answer are generated according to:

$$V_i = \sum_{j=1}^{5} \mathrm{PRBM}_j \; v_{i,j},$$

where:

i = index from 1 to the number of elements in the union of volumes in all models,

j = individual model number,

$v_{i,j}$ = volume of mineral i found in model j,

PRBM_j = probability of individual model j, and

V_i = volume of mineral i in the combined answer set.

Normally, the probability functions approximate step functions so that only one of the individual models is valid at a particular depth level. This is true when the individual models represent different rock types with a sharp interface, as in an evaporite overlying a shale. When the models are similar and represent end members of a sequence as in shaly sand and shale models, the functions can be set up with a smooth transition.

AN EXAMPLE - COMPLEX LITHOLOGY

Example 1 is a well from the Permian basin that was logged through the Yates formation using the Litho-Density, CNL*, NGS, EPT*, and BHC tools. The reservoir consists of shaly sands with interspersed tight carbonate streaks. Evaporite sequences consisting of anhydrite and halite lie above the reservoir section. Three individual models were defined:

CARBONATE – A reservoir model consisting of calcite, anhydrite, dolomite, illite, feldspar, oil, and water.

SAND – A second reservoir model consisting of quartz, calcite, dolomite, illite, feldspar, oil, and water.

EVAPORITE – A model consisting of halite, anhydrite, dolomite, illite, and water. No oil is allowed in this model.

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The individual models and probabilities were defined as shown below:

Model	Volumes	Log Inputs	Probability Function
1	ANH DOL CAL ILL FEL OIL WAT	RHOB NPHI U THOR POTA TPL	1 when the probabilities of Models 2 and 3 are zero.
2	ILL QUA FEL DOL CAL OIL WAT	RHOB NPHI U THOR POTA TPL	1 when ILL + KAO + QUA $\geq$ 0.15
3	HAL ANH ILL DOL WAT	RHOB NPHI U THOR POTA	1 when HAL $\geq$ 0.35 0 when ILL $\geq$ 0.10

Table 3

To the right of the volumetric display for each model is a narrow track where the incoherence (dark gray pattern) and probability function (dotted pattern) are displayed on a scale of one to zero (left to right). From 2584 to 2496 ft the SAND model is selected by the probability function. In this interval the incoherences for the CARBONATE and EVAPORITE models are large because quartz exists in the formation and is not defined in these models.

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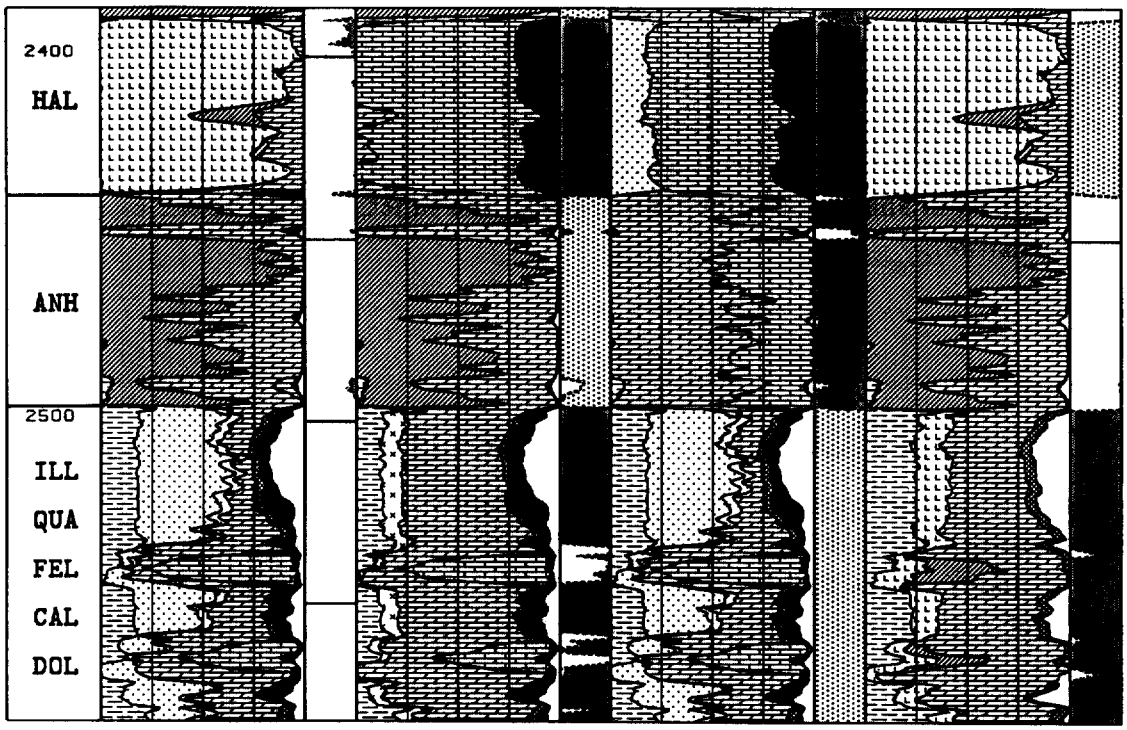

Fig. 2

From 2496 to 2448 ft the probability function selects the CARBONATE model. In this interval the incoherence for the SAND model is large because anhydrite is present in the formation and is not defined in the SAND model. The EVAPORITE model is invoked from 2403 to 2448 ft.

PARAMETER CALIBRATION

The sonic tool was not used in the interpretation. Using a set of default values, volumes from the combined answer were used to generate a synthetic sonic log. This synthetic log DTT is compared against the measured sonic log DT in the left-hand track of the next display. Note that although the general character of the two logs is similar there is considerable disagreement. The conventional technique of selecting correct parameters is to make an estimate of the change required and run the program again. By an iterative process one may eventually converge on appropriate parameters.

The parameter estimation program CALPAR can infer the optimum parameters in one pass. The results of the computation using the output volumes calculated above are shown in Table 4.

Mineral	Default Parameters	CALPAR Parameters
QUA	55.5	55.3
HAL	67.0	66.4
CAL	50.5	51.2
DOL	46.0	45.3
ANH	50.0	51.7
ILL	100.0	94.0

Table 4

The sonic parameters derived from the CALPAR program were used together with the volumes from the combined answer set to generate a second synthetic log. The results are shown in the middle track of the display. Observe the excellence of the fit between the synthetic log and the measured log.

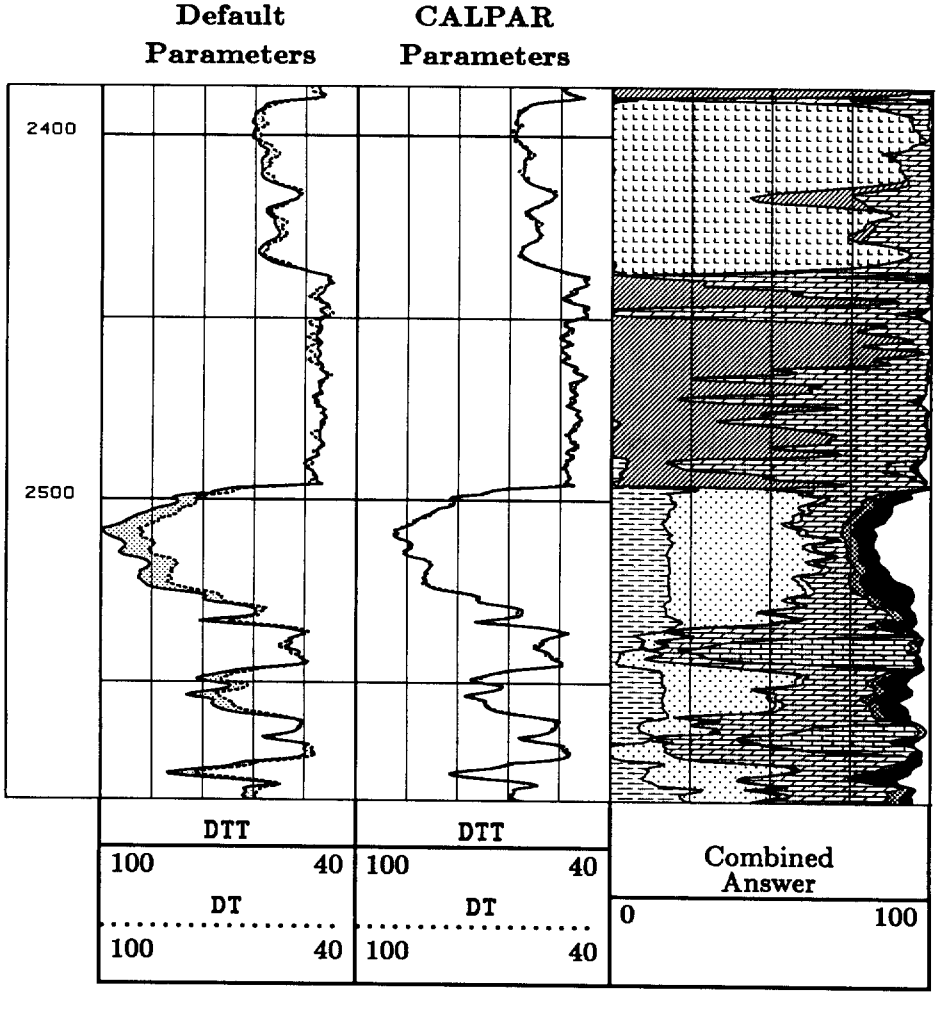

Fig. 3

AN EXAMPLE - THE SARABAND* MODEL

The early SARABAND computer program was very successful for the evaluation of shaly-sand sequences. See Reference 4 for a thorough explanation. Apart from statistical zoning features the program embodied a particular method of using the neutron-density crossplot. This method was based on the premise that clastic sequences obeying the model consisted of two rock types – shaly-sands and shales, which correspond to the trends indicated on the mineral ternary diagram on the left below:

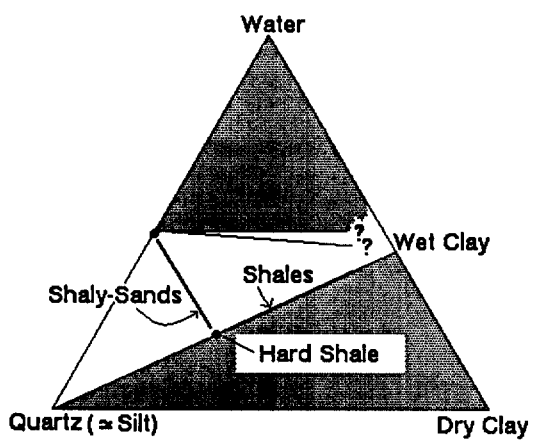

Fig. 4a

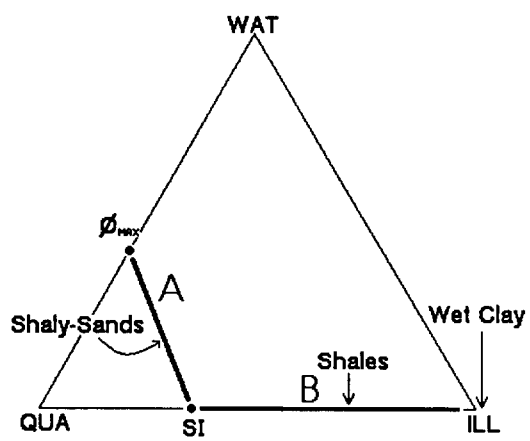

Fig. 4b

This is translated into the symbols used in the ELAN program in the diagram on the right. Note that `WAT` is the 'far' water of the dual-water model[5] and that `ILL` is 'wet' illite, which incorporates clay-bound water.

The example below is from a Gulf Coast gas well. A 'sequence model' for this well is created by using three individual models; a shaly-sand with gas, a shale, and a shaly-sand with gas and calcite cement. Line A in the SARABAND model is broadened to a range of porosity between 0.35 and 0.40 by the use of inequality constraints.

Model	Description	Components	Inputs	Constraints
1	Shaly Sand	QUA ILL WAT GAS	RHOB NPHI DT GR RT	WAT + GAS $\geq$ 0.35 WAT + GAS $\leq$ 0.40
2	Shale	QUA ILL WAT	RHOB NPHI DT GR	WAT = 0
3	Cemented Sand	QUA ILL CAL WAT GAS	RHOB NPHI DT GR RT	QUA + CAL $\geq$ 0.60

Table 5

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Note that shaly-sand and shale trends are present but that shale points are affected by rugose hole and that there are some calcite cemented sands.

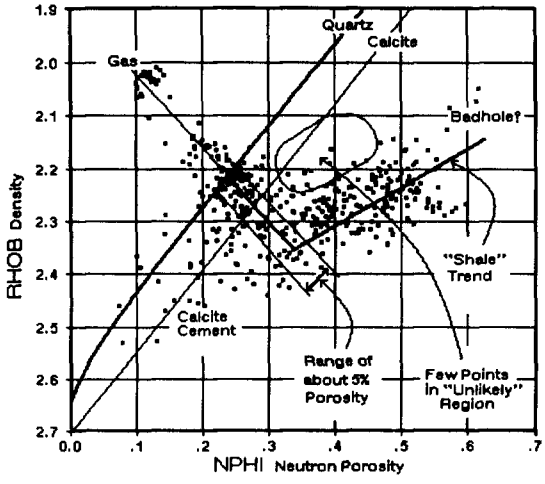

Fig. 5

The result of combining these three models over a 90-ft sequence can be seen in the figure below:

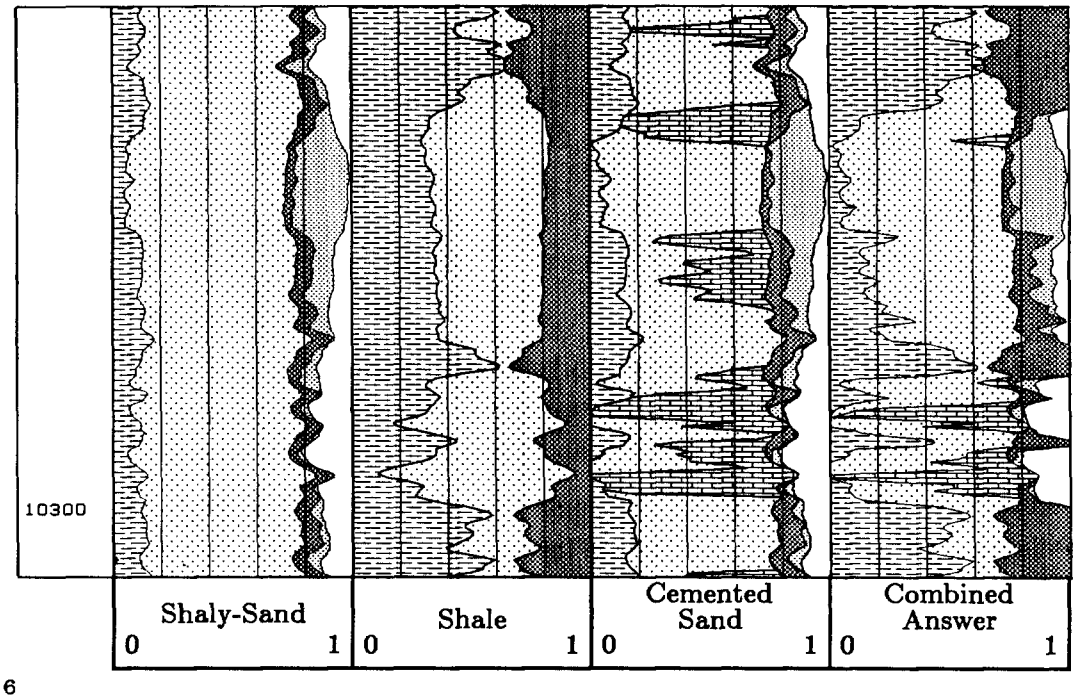

Fig. 6

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The model-switching criteria are simply that Model 2 is used whenever ILL $\geq$ 0.35, with 100% probability when ILL = 0.40, and that Model 3 should be used when ILL $\leq$ 0.10. This is justified because ILL in Model 2 is essentially responding to silt index, and calcite cement only occurs in clean sands.

In the display below, reconstructed logs have been generated and compared with input logs over the same interval.

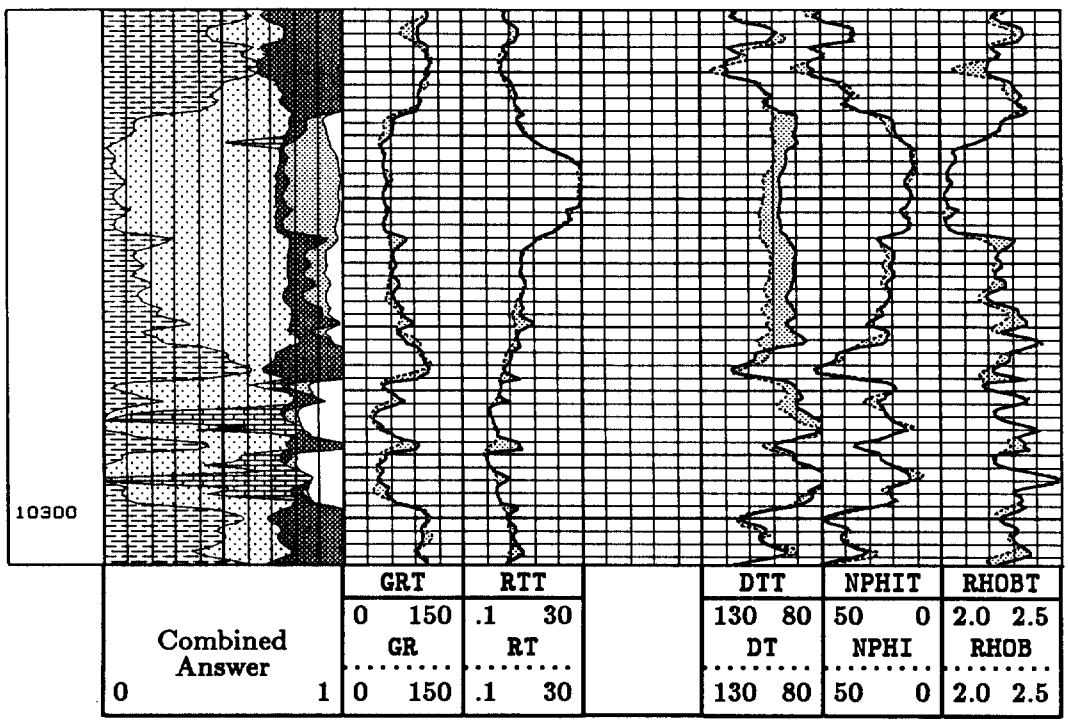

Fig. 7

Note that the sonic log reconstructs poorly over the interval 10236 to 10273 ft. This is due to a deficiency in the Wyllie time-average equation when gas is present, and it is not a parameter calibration effect as shown in the previous example.

Note also the 'spikiness' of the reconstructed resistivity log compared to the original, which is derived from a deep induction measurement. The slow vertical response of the induction cannot track the rapid variations in lithology and porosity seen by the nuclear tools. This problem commonly results in hydrocarbons appearing in shales whenever conductivity is too low because of thin-bed effects. Programs with simple fixed models resort to 'saturation boosting' cosmetics in order to eliminate phantom shows.

CONCLUSION

A coherent framework has been designed within which quantitative formation evaluation models can be developed, tested, applied, and combined.

Existing formation evaluation software uses either transform or inverse methods. Transform methods are limited in their ability to use new data and have inflexible models. Inverse methods can in principle use any data inputs, but to date they still have many implicit model assumptions and provide no means for model selection and verification. The programs described here provide several new features:

- A general framework is provided that solves the forward problem and the parameter estimation program as well as the traditional inverse problem. These two features allow the quantitative use of geological knowledge and improve the efficiency and accuracy of determining tool response parameters.

- Automatic combination of models makes it practical to use very explicit models for each facies. This avoids the need for cosmetics and vaguely defined parameters that are needed to adapt general models to specific formations.

- Fast solution of the inverse problem improves efficiency and makes it feasible to run several individual models in parallel.

- The user interface provides a rational viewpoint in terms of mineral and fluid volumes, which allows easier links between formation evaluation and geology.

These features provide a powerful means for all types of formation evaluation.

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GLOSSARY OF MNEMONICS AND SYMBOLS

RHOB	– Density log	CAL	– Calcite
RHOBT	– Reconstructed density log	DOL	– Dolomite
NPHI	– Neutron log	QUA	– Quartz
NPHIT	– Reconstructed neutron log	ANH	– Anhydrite
GR	– Gamma ray log	HAL	– Halite
GRT	– Reconstructed gamma ray log	ILL	– Illite
DT	– Sonic Δt log	FEL	– Feldspar
DTT	– Reconstructed sonic log	WAT	– Water
THOR	– Thorium log	OIL	– Oil
POTA	– Potassium log	GAS	– Gas
TPL	– Electromagnetic propagation time log	BWA	– Bound Water

U	–	Photoelectric absorption cross section per volume
$\mathbf{t}$	–	Tool measurements vector
$\hat{\mathbf{t}}$	–	Reconstructed tool vector
$\mathbf{v}$	–	Volumetric components vector
$\mathbf{R}$	–	Response parameter matrix
$\mathbf{D}$	–	Uncertainty values matrix
inco	–	Disagreement between reconstructed and tool vector
^{T}	–	Matrix transpose operation
$\hat{\rho}_b$	–	Synthetic density log
ϵ	–	Noise or statistical variation parameter
t_i	–	The ith component of the tool vector $\mathbf{t}$
PRBM_i	–	Probability of the ith individual model
v_i	–	The ith component of the volume vector $\mathbf{v}$
c_i	–	Volume coefficient in inequality
d_i	–	Tool coefficient in inequality

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