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Global inversion of well log data

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A global optimization method for solving the nonlinear geophysical well-logging inverse problem is presented. At first a conventional point by point inversion method using local response equations is applied to estimate, separately, the petrophysical parameters (effective porosity, water saturation, shale and matrix contents) at different depths. In addition, I introduce the so-called interval inversion procedure, which uses all the data in a greater depth-interval in a joint inversion process. To test and compare the inversion methods synthetic and field well log data are inverted. The results show that the interval inversion algorithm is more powerful and yields more accurate petrophysical parameters than the local point by point inversion method. The former results in much more accurate and reliable parameter estimation and also gives an estimate for the layer-thicknesses as an additional item of geological information that up till now could not have been treated as an unknown in geophysical well-logging inversion.

Keywords: optimization, inverse problem, petrophysical parameters

1. Introduction

The role of geophysical well-logging is to inform us about the geometrical position and petrophysical properties of the rocks traversed in the borehole. To determine these parameters modern inversion methods can be used with the application of up-to-date informatics. The unknowns of the nonlinear inverse problem are characteristic petrophysical values, where a few parameters have a constant value in a layer, and several parameters are invariable in the zone investigated. The layer-thicknesses might also be treated as unknowns, but the conventional point by point inversion technique, which uses the well log data set separately, cannot handle this problem. Thus the layer boundary-coordinates can be determined only in a pre-inversion procedure. In practice, point by point inversion is generally used to interpret the measured data. Most point inversion procedures are based on linearized optimization methods and give a weighted least squares (LSQ) solution. If we have satisfactory a priori information about the

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petrophysical model, they work as a very quick and effective algorithm. However, being gradient methods if extensive inversion problems arise they can probably assign the solution to a local optimum of the objective function. This problem is solved by the global optimization methods that search the absolute extremes of the objective function with much higher probability than linearized optimization methods. The most preferred global optimization procedures are Simulated Annealing and Genetic Algorithms.

2. The forward problem

In formulating the forward problem let us introduce the column vector of the petrophysical model parameters at a certain depth-point as

$$\vec{m} = \{POR, SX0, SW, VSH, VSD, VLM\}^T \quad , \tag{1}$$

where *POR* denotes the effective porosity, *SX*0, *SW* denote the water saturation in the invaded and the virgin zone, *VSH, VSD, VLM* denote the specific volume of shale, sandstone and limestone. To determine the model parameters we utilize logs measured in the borehole that record various parameters of natural and induced physical fields as a function of depth. The following transposed vector contains the observed data of a possible combination of well logs at a certain depth

$$\vec{d}^{(obs)} = \{SP, GR, PORN, DEN, AT, RMLL, RLLD\}^T \quad , \tag{2}$$

where *SP* [mV] represents the spontaneous potential, *GR* [API] denotes the natural gamma-ray, *PORN* [p.u. (porosity unit)] denotes the neutron porosity, *DEN* [gcm^{-3}] denotes the bulk density, *AT* [μsm^{-1}] denotes the acoustic traveltime, and *RMLL*, *RLLD* [ohmm^{-1}] denote the micro- and deep laterolog resistivity data. The measured data reflect the immediate vicinity of the borehole. The *SP, GR* logs are mainly sensitive to the lithology, *PORN, DEN, AT* logs indicate the porosity, and *RMLL, RLLD* data are primarily influenced by the water saturation. Since the measurement is carried out in relatively complicated borehole surroundings we need to create a petrophysical model of the formation of interest on the basis of the corrected observed data set and the available a priori information. In the next step we calculate data by means of the petrophysical parameters of the relevant model by certain petrophysical relationships. These latter are

called response functions and they connect the model parameters with the well log data used for solving the direct problem. Through the set of response functions there is a connection between the predicted model parameter vector and the calculated data vector, viz.

$$\vec{d}^{(calc)} = \vec{g}(\vec{m}, \vec{c}) \quad , \tag{3}$$

where $\vec{c}$ denotes the vector of textural constants and zone parameters. The choice of the response functions depends on the depth and the petrophysical properties of the formation investigated. (The interpreter can find many kinds of detailed empirical equations in handbooks). In forward modelling we substitute the initial (and later the estimated) values of the model parameters of Eq. (1) into Eq. (3), then the data obtained are compared with the observed data set to make a prediction for the petrophysical model by an inversion method. Obviously, the set of response equations is nonlinear with regard to the model parameters, but we can transpose the direct problem relatively quickly to other geophysical problems that have generally simple structured equations. Thus it is advantageous to solve the inverse problem by means of a global optimalization method.

3. Inversion algorithms

To solve the nonlinear geophysical well-logging inverse problem a point by point inversion method is conventionally used, which utilizes the data set of a certain depth-point to determine the petrophysical model parameters for the given point. Under the procedure we consider the adjacent depth-points to be independent from each other using local response equations to calculate the theoretical well log data. Therefore we cannot determine the layer-thicknesses by this method. The inverse problem can be solved by the minimization of the error between the observed and the calculated data having a marginally overdetermined system.

The theoretical data at the depth-point are calculated by means of a local set of response equations of Eq. (3). The calculated vector data of the jth log can be written in a general form as

$$d_j^{(calc)} = g_j(m_1, \ldots, m_M) \tag{4}$$

where M denotes the number of model parameters at the point.

Since the number of observed data is slightly more than the number of unknown model parameters at the point, the accuracy and the reliability of

the estimations are relatively limited. For Eqs. (1) and (2) there are 6 petrophysical parameters against 7 well log data, so it is worth inverting data of a greater interval jointly in one inversion procedure. The so-called interval inversion algorithm is based on the series expansion of the petrophysical parameters, which develops depth-dependent layer characteristic parameters [DOBRÓKA 1995]. With appropriate series expansion the relation in Eq. (4) modifies to a response function interpreted in a depth-interval. The synthetic data calculated from the jth log at depth z is

$$d_j^{(calc)}(z) = g_j\left(B_1^{(1)},\ldots,B_{Q_1}^{(1)},\ldots\ldots,B_1^{(M)},\ldots,B_{Q_M}^{(M)},Z_1,\ldots,Z_n,z\right), \qquad (5)$$

where B denotes the unknown discretization coefficients with Q number of discretization coefficients required for the development of any model parameter, and Z_1, ..., Z_n represent the layer boundary co-ordinates that can be chosen as unknown model parameters. By interval inversion we can determine the B coefficients in order to approximate the petrophysical model parameters in Eq. (1) along the whole observed interval.

4. Global optimization method – Simulated Annealing

Linearized inversion methods are the most used for inversion, because for an initial model that is near to the solution they are very quick and effective algorithms and are also capable of checking the quality of the estimated model parameters. But as they are not absolute minimum searching methods, they generally assign the solution to a local optimum of the objective function. This problem is solved by the Simulated Annealing (SA) method, which performs the global optimization of the objective function by random walking in the parameter space. SA was first proposed by METROPOLIS et al. [1953] to model the thermal equilibrium state of solids.

In metallurgy the removal of the effect of work-hardened solids is realized by a slow cooling process from the temperature of the liquid alloy. This process reduces progressively the kinetic energy of a large number of atoms with high thermal mobility before crystallization. Theoretically, the perfect crystal grating, which has minimal overall atomic energy is produced by an infinitely slow cooling process. This is analogous to the stabilization in the global optimum of the objective function of a geophysical inverse problem. A quicker cooling operation for that causes grating de-

fects, where the solid freezes in an imperfect grid with a higher energy state. It is similar to the stagnation of the inversion process at a local minimum of the objective function (generally known as energy function). However, atoms may escape from this higher energy state owing to a special annealing process and after that — by means of slow cooling — the optimal crystal grating can be achieved. The SA-method uses this procedure to search for the global optimum of the energy function.

The MSA-algorithm (SA based on the Metropolis algorithm) modifies the components of the relevant model parameter vector in every iteration step. The modification of the *j*th model parameter can be performed by means of

$$m_j^{(new)} = m_j^{(old)} + b$$

where b denotes an actual perturbation term. This small number can be varied between $[b, b_{max}]$, where b_{max} is generally decreased by

$$b_{max}^{(new)} = b_{max}^{(old)} \cdot \varepsilon$$

after a specified number of iteration steps ($0 \le \varepsilon \le 1$). During the random walk in the parameter space the energy function of the relevant model is calculated and compared with the previous one in every iteration step. The acceptance probability *(P)* of the new model depends on the Metropolis criterion

$$P(\Delta E, T) = \begin{Bmatrix} 1 & , \ if \ \ \Delta E \le 0 \\ \exp(-\Delta E / T) & , \ if \ \ \Delta E > 0 \end{Bmatrix}$$

where T denotes a temperature which must be reduced by $T(new)=T(old) / \ln(actual\ iteration\ step)$ during the search to achieve the global optimum [GEMAN, GEMAN 1984]. It is clear that if the energy is lower in the new step than in the previous one, we always accept the new model. Otherwise if the energy of the new model had been increased, there would also be a probability of acceptance depending on the value of the energy needed to escape from the local minimum. If $P(\Delta E) \ge \alpha$ is fulfilled (where α is generated with uniform probability from [0,1]), then the new model parameters are accepted otherwise we reject them. The convergence of the inversion is largely influenced by the cooling process applied. We must avoid too rapid cooling because the solution can be frozen at a local minimum, but neither should there be too slow cooling because of unnecessarily increasing the CPU time.

4.1. Global point by point inversion

Let us define the objective function, i.e. energy function of the inverse problem. If our data are charged with Gaussian noise we can choose optimally to minimize

$$E_2 = \frac{1}{L}\sum_{i=1}^{L}\left(\frac{d_i^{(obs)} - d_i^{(calc)}}{d_i^{(obs)}}\right)^2 \rightarrow \min \tag{6}$$

which is based on the principle of the LSQ-method. The quality of inversion results are characterized separately at every depth-point by the following relative model and data distances [DOBRÓKA et al. 1991]

$$Ddata = \sqrt{\frac{1}{L}\sum_{j=1}^{L}\left(\frac{d_j^{(obs)} - d_j^{(calc)}}{d_j^{(obs)}}\right)^2} \cdot 100[\%]$$

$$D\mathrm{mod} = \sqrt{\frac{1}{M}\sum_{k=1}^{M}\left(\frac{m_k^{(est)} - m_k^{(exact)}}{m_k^{(exact)}}\right)^2} \cdot 100[\%] \tag{7}$$

Determination of the reliability of the estimated parameters for global optimization methods is different from the event of linearized optimization. To get useful information about the statistics of the model parameters determined it is nowadays a problem of several orders of magnitude longer computational run time. Here I did not deal with this problem, but we are working on a new technique to solve it.

4.2. Global interval inversion

The energy function of the interval inversion problem is the following for Gaussian data noise

$$E_2 = \frac{1}{DP \cdot L} \sum_{h=1}^{DP} \sum_{i=1}^{L} \left(\frac{d_{hi}^{(obs)} - d_{hi}^{(calc)}}{d_{hi}^{(obs)}} \right)^2 \rightarrow \min , \tag{8}$$

where DP denotes the number of depth points in the processed interval. If we also have outliers in the data set it is better to choose the following norm for optimization, which is equivalent to the known Least Absolute Deviations (LAD) method

$$E_1 = \frac{1}{DP \cdot L} \sum_{h=1}^{DP} \sum_{j=1}^{L} \left| \frac{d_{hj}^{(obs)} - d_{hj}^{(calc)}}{d_{hj}^{(obs)}} \right| \rightarrow \min . \tag{9}$$

The inverse problem is now largely overdetermined, therefore we can also determine the co-ordinates of the formation boundaries automatically by the interval inversion algorithm based on Eq. (5). The petrophysical and the geometric parameters of the formations can be obtained by optimizing Eq. (8). The quality of the inversion results is characterized in the whole depth interval processed by the following relative model and data distances

$$Ddata = \sqrt{\frac{1}{DP \cdot L} \sum_{h=1}^{DP} \sum_{j=1}^{L} \left(\frac{d_{hj}^{(obs)} - d_{hj}^{(calc)}}{d_{hj}^{(obs)}} \right)^2} \cdot 100[\%]$$

$$Dmod = \sqrt{\frac{1}{R \cdot M} \sum_{r=1}^{R} \sum_{k=1}^{M} \left(\frac{m_{kr}^{(est)} - m_{kr}^{(exact)}}{m_{kr}^{(exact)}} \right)^2} \cdot 100[\%] \tag{10}$$

where R denotes the number of layers in the interval involved in the inversion. In the computation, a layer-wise homogeneous model is assumed.

5. Numerical results

In order to test and compare the inversion algorithms based on the Simulated Annealing method, noisy synthetic well log data were generated as quasi-measured input data. After processing them optimal petrophysical

parameters were estimated and the diagnostic values of Eqs. (7) and (10) were calculated to characterize the algorithms from the point of view of accuracy. Furthermore, measured well log data collected in a Hungarian borehole were also interpreted in order to prove that the global inversion methods can be utilized for real geological structures as well.

5.1. Generation of synthetic data sets

To invert noisy synthetic well log data a series of strata that consists of four homogeneous sedimentary layers was defined. The petrophysical parameters of the model are shown in *Table I*, where *H* denotes the layer thickness [m], *POR* denotes the effective porosity [fraction], *SX0* denotes the water saturation in the flushed zone [fraction], *SW* denotes the water saturation in the virgin zone [fraction], *VSH* denotes the shale content [fraction], *VSD* denotes the sand content [fraction], and *VLM* denotes the limestone content [fraction].

H (m)	*POR*	*SX0*	*SW*	*VSH*	*VSD*	*VLM*
8.0	0.2	1.0	1.0	0.1	0.7	0
5.0	0	1.0	1.0	0.9	0.05	0.05
10.0	0.3	0.8	0.5	0	0.7	0
6.0	0.1	1.0	1.0	0.5	0.3	0.1

Table I. Four-layered petrophysical model
I. táblázat. Négyréteges kőzetfizikai modell

Synthetic data were calculated for this four-layered model. In *Fig. 1a, b* synthetic well logs can be seen from Eq. (2) charged with 5 per cent Gaussian noise. In addition to the 25 per cent of these data, random noise was added to simulate well logs charged with outliers. In Fig. 1a, b the curves with outliers are represented by a grey line in the same diagram.

5.2. Inversion of synthetic data sets

The petrophysical parameters estimated by point by point inversion based on the MSA method were determined by the optimization of Eq. (6) for fixed layer boundary-coordinates. At this point there were only 7 data against 6 model parameters. In *Fig. 2*, it can be seen that very different values of the model parameters were obtained in the same layer because of the narrow type of overdetermination and the noise propagated from the data space to the model space. Petrophysical parameters estimated by the

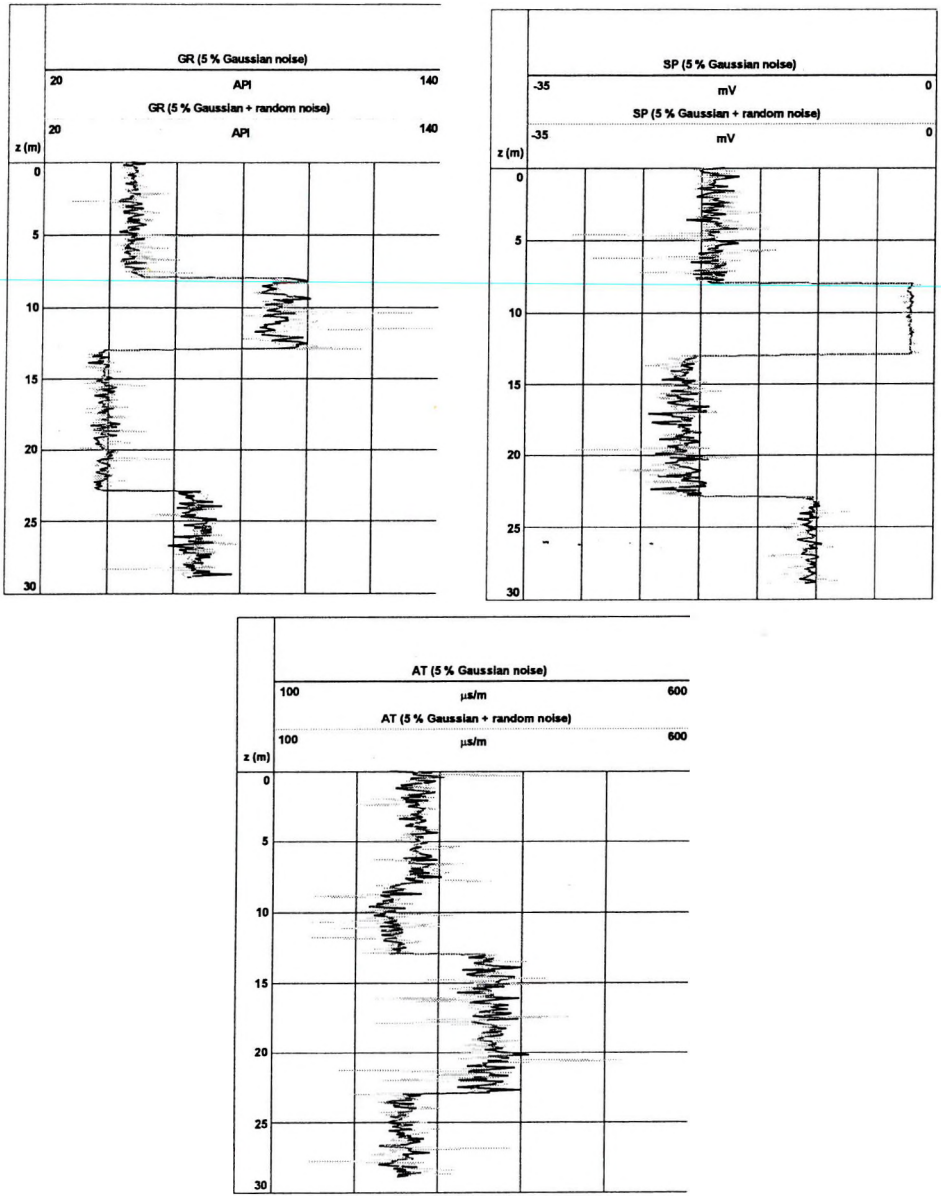

Fig. 1a. Synthetic data set charged with 5% Gaussian noise and 5% Gaussian plus random noise. GR: natural gamma ray log; AC: acoustic traveltime log; SP: spontaneous potential log

1a. ábra. 5% Gauss zajjal és 5% Gauss + véletlen zajjal terhelt szintetikus karotázs szelvények. GR: természetes gamma szelvény; AC: akusztikus terjedési idő szelvény; SP: természetes potenciál szelvény

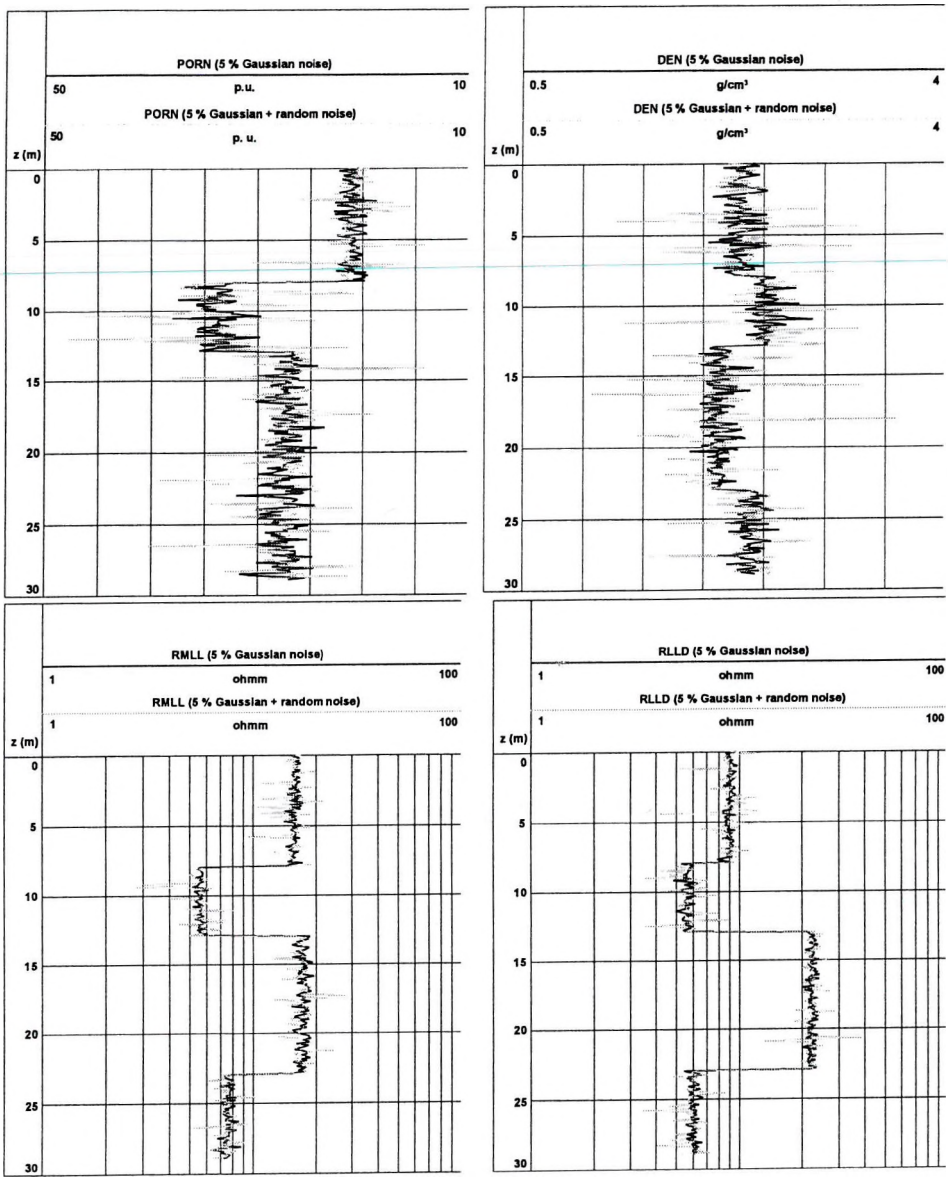

Fig. 1b. Synthetic data set charged with 5% Gaussian noise and 5% Gaussian plus random noise. PORN: neutron porosity log; DEN: density log; RMLL: microlaterolog; RLLD: deep laterolog

1b. ábra. 5% Gauss zajjal és 5% Gauss + véletlen zajjal terhelt szintetikus karotázs szelvények. PORN: neutron-porozitás szelvény; DEN: sűrűség-szelvény; RMLL: mikrolaterolog szelvény; RLLD: mélybehatolású laterolog szelvény

point by point inversion method are loaded with relatively high uncertainty, which is not a very advantageous feature concerning the estimation of the moveable hydrocarbon saturation (*SCHM=SX0–SW*) in the third bed (*SCMR=1–SX0* means hydrocarbon saturation that cannot be produced). The relative data and parameter distances from Eq. (7) can be found in *Table II*, where 'o' means that there are outliers in the data set. The MSA-procedure always gave initial model independent and convergent solutions. In comparison with the linearized LSQ-method, which was also tested on this model (and gave 10.52 per cent for *Ddata*, and 5.69 per cent for *Dmod*), it was found that global optimization improves the accuracy of the estimated model.

Well log data (noise)	Inversion algorithm	Layer-thickness	Energy function	*Ddata* (%)	*Dmod* (%)
Synthetic (5%)	Separated	Fixed	E_2	5.65	9.65
Synthetic (5%)	Interval	Fixed	E_2	5.03	1.89
Synthetic (5% + o)	Interval	Fixed	E_2	13.41	6.62
Synthetic (5% + o)	Interval	Fixed	E_1	7.54	2.75
Synthetic (5%)	Interval	Unknowns	E_2	5.11	2.20
Measured	Separated	Fixed	E_2	4.82	—
Measured	Interval	Fixed	E_1	5.98	—
Measured	Interval	Unknowns	E_1	6.06	—

Table II. Accuracy of inversion results estimated by MSA inversion methods
II. táblázat. MSA inverziós módszerrel becsült inverizós eredmények pontossága

Besides constant layer-thicknesses the interval inversion can also be found in Table II. For the determined model there were 2030 data against 24 unknowns in the total inverted depth-interval. Thus over-determination was highly increased in comparison with point by point inversion. It can be seen in Fig. 2 that interval inversion resulted in much more accurate parameter estimation with better stability. Relative data and model distances used are formulated by Eq. (10).

With regard to interval inversion it is pointed out that there is a five times better result compared with point by point inversion, which implies a very accurate and reliable algorithm. On the other hand, the linearized LSQ

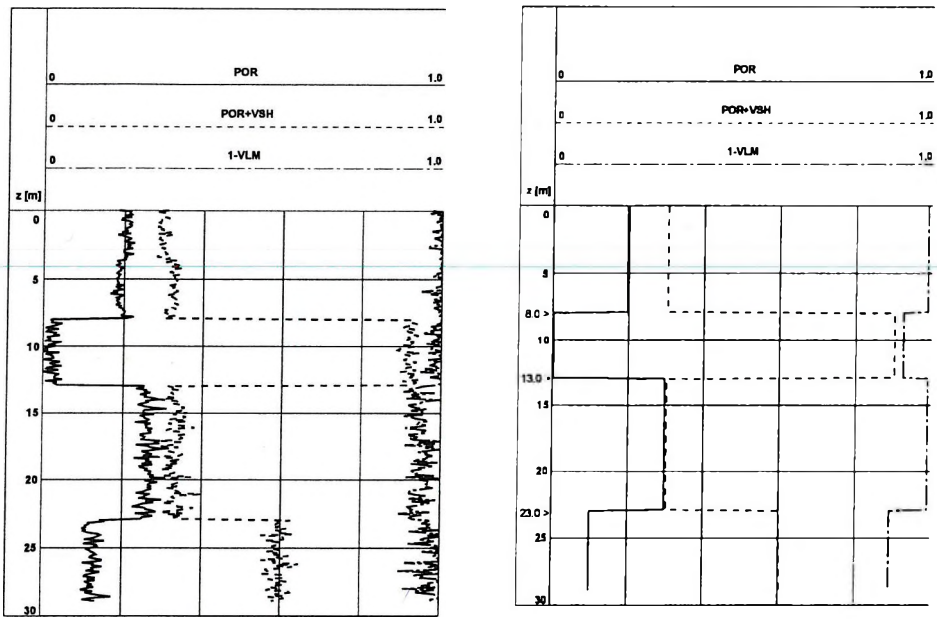

Fig. 2. Point by point and interval inversion results. On the right the estimated layer-boundary co-ordintaes are also represented in depth scale

2. ábra. Mélységpontonkénti és intervallum inverziós eredmények. A jobb oldali ábra mélységskáláján a becsült réteghatár-koordináták szerepelnek

interval inversion method was also tested (giving 2.27 per cent for *Dmod*) and proved less powerful than the global interval inversion procedure. Moreover, in practice it is possible that there are outliers in the well-log data set. Let us analyse the interval inversion of synthetic data charged with outliers. At first let us optimize the energy function (Eq. (8)) and then apply Eq. (9), which is well known for its resistance against outliers. The data distance is also defined in Eq. (9). From Table II it can be seen that there are adequate results despite the existence of outliers. Thus it can be stated that the MSA technique can be made resistant by way of selecting the objective function based on Eq. (9).

Let us take layer-thicknesses into account as unknown model parameters in the interval inversion process. In Table II, it can be seen that the accuracy of model parameter estimation is quite as good as interval inversion given that there are fixed layer boundary-coordinates. These results are still four times more accurate than those from point by point inversion. The interval inversion procedure was stable and resulted in very

accurate parameter estimation for both the layer thicknesses and the petrophysical parameteres. It is also important to mention that the layer thicknesses as unknown model parameters converged primarily to their expected values. The exact layer-thickness values of the inversion model were achieved approximately in the 3000th iteration step, where the total number of iteration steps was 200000. They were followed by the petrophysical model parameters giving a very accurate solution of the interval inversion problem. As a consequence, the MSA interval inversion method is able to estimate more accurate hydrocarbon saturation than the linearized point by point inversion method; this feature is highly important in petrophysical practice.

6. In-situ results

To invert in-situ well log data 6 logs measured in a Hungarian borehole were chosen. Four unconsolidated sedimentary layers were investigated, where the sand bed in between was a water-bearing formation with a relatively high porosity and a little amount of shale. Supposing a simple lithology *POR, VSD, VSH* volumetric petrophysical parameters were treated as unknowns for the fixed values of *SX0* and *SW*. The input data set was composed of the corrected values of *SP, GR, DEN, RMLL, CNC* (compensated neutron), *RILD* (deep induction) well logs. The data set can be seen in *Fig. 3a, b*, and the results of point by point and interval inversion in case of unknown layer-thicknesses are given in *Fig. 4*.

For point by point inversion there were 3 unknowns against 6 data per depth point. Altogether there were data from 195 points. In the case of interval inversion we had to determine 12 volumetric petrophysical parameters and a further 3 boundary-coordinates of the formations. Table II shows that the fitting in data space is satisfactory and the tendency is analogous with that of the inversion of synthetic data. From the point of view of forward modelling more accurate parameters can be obtained by choosing more appropriate response functions and textural constants. Interval inversion can be developed by making a more suitable series expansion, which better describes the vertical changes of the petrophysical parameters in the computed interval. Lastly, the interval inversion method has a considerable advantage over point by point inversion as it determines automatically the layer-thicknesses. The layer boundary-coordinates were

obtained at 8.1, 13.5 and 16.5 meters (the depth-coordinates were transformed as the top of the first layer could be at zero level) as can be seen in Fig. 4.

7. Conclusions

It was shown that the global inversion of well log data based on the MSA method results in a correct solution that is independent of the initial model. However, it is important to emphasize that the convergence of the global optimization process is largely influenced by the setting of control parameters of the Simulated Annealing algorithm (e.g. initial temperature, cooling process) and choosing a proper fitting function to minimize.

A disadvantage is that MSA requires more computer time than linearized optimization methods.

It was shown that it is more advantageous to use the interval inversion method by determining the layer-thicknesses than point by point inversion. It utilizes more information from the observed data and can be improved by

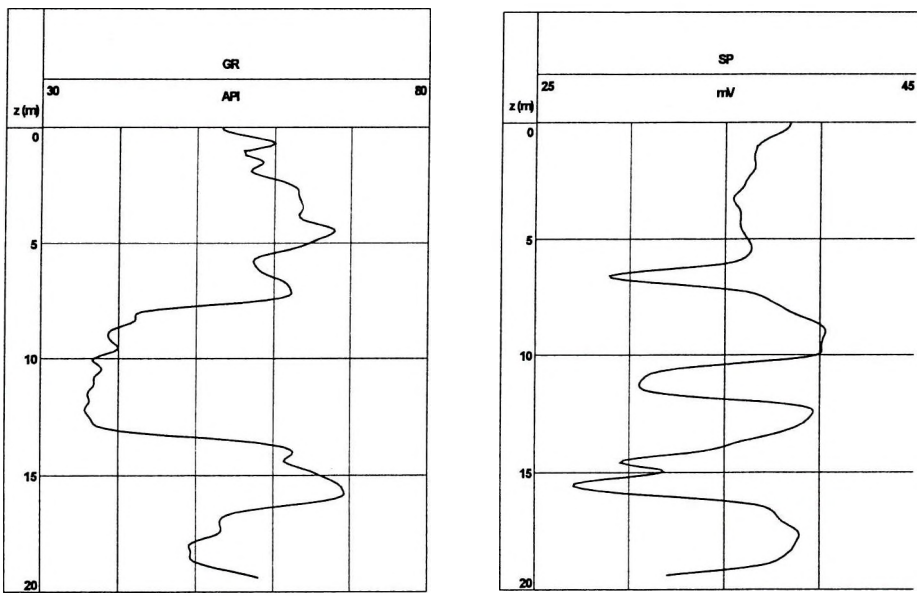

Fig. 3a. Measured well log data inverted. GR: natural gamma ray log; SP: spontaneous potential log

3a. ábra. Terepi mérési szelvények. GR: természetes gamma szelvény, SP: természetes potenciál szelvény

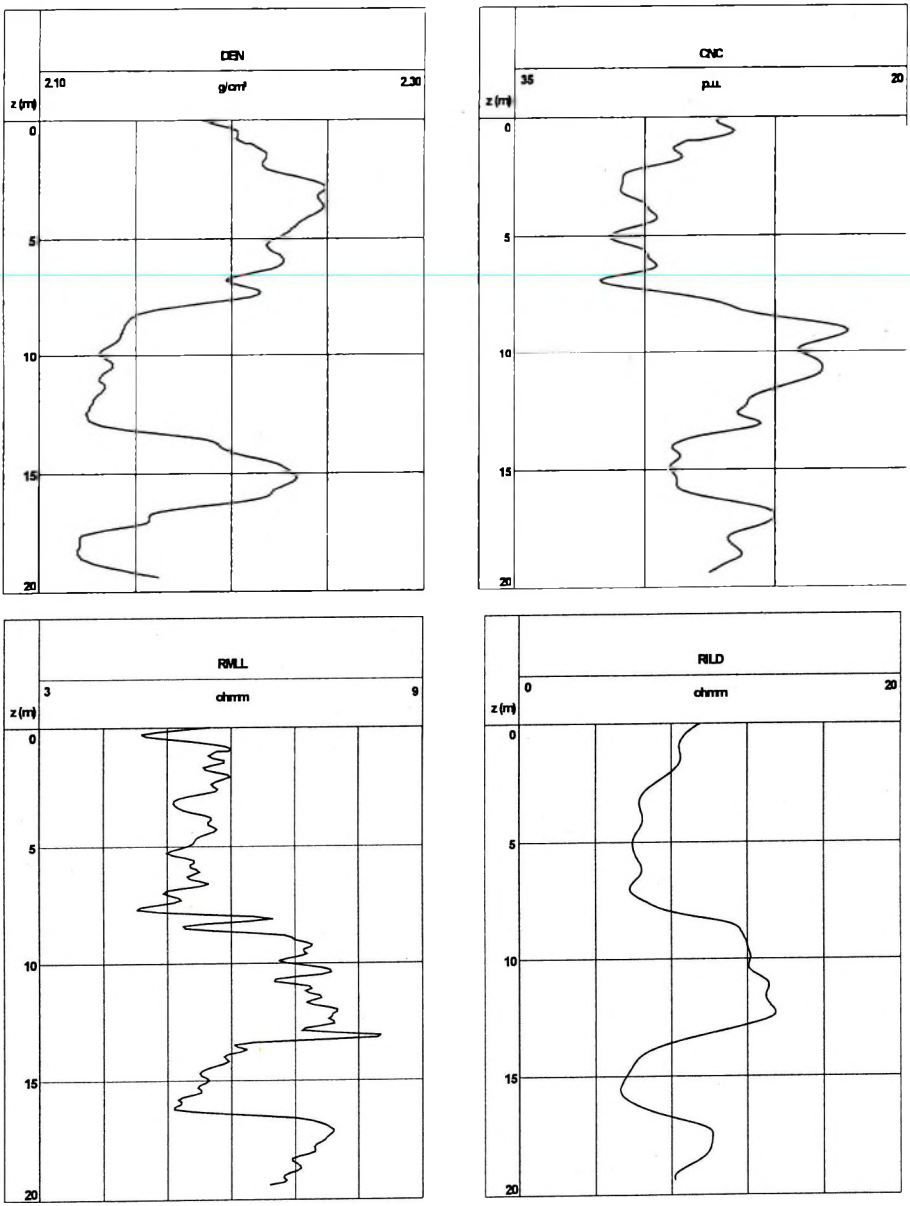

Fig. 3b. Measured well log data inverted. DEN: density log; CNC: compensated neutron porosity log; RMLL: microlaterolog; RILD: deep induction log

3b. ábra. Terepi mérési szelvények. DEN: sűrűség szelvény; CNC: kompenzált neutron-porozitás szelvény; RMLL: mikrolaterolog; RILD: mélybehatolású indukciós szelvény

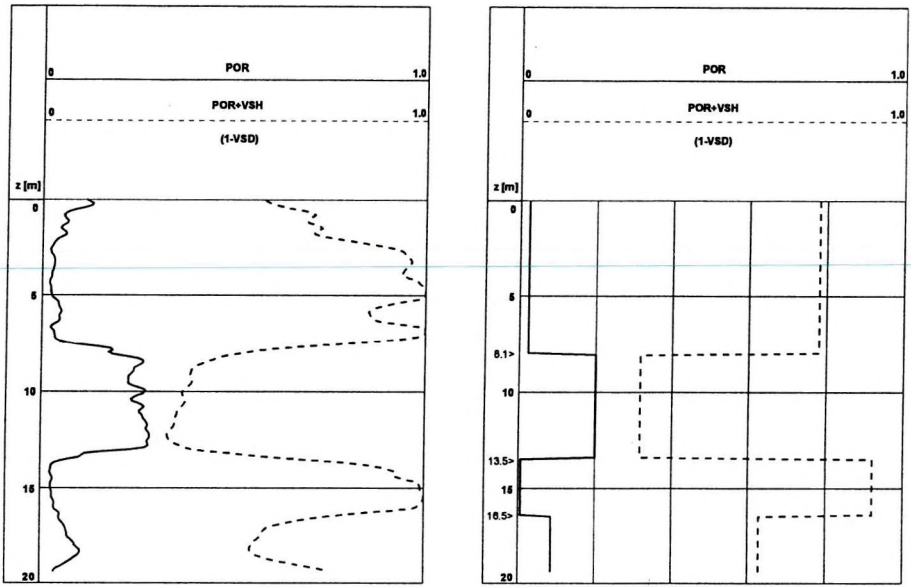

Fig. 4. MSA point by point and interval inversion results
4. ábra. MSA mélységpontonkénti és intervallum inverzió eredmények

choosing more suitable basis functions in the series expansion of petrophysical model parameters. The vertical changes of porosity, saturation, shale and matrix volumes can be derived in one inversion procedure by appropriate series expansion. Moreover the interval inversion procedure is able to give an estimate for the layer thicknesses. Thus it offers much greater promise in terms of yielding more geological information about the geological structure investigated in the borehole.

REFERENCES

DOBRÓKA M., GYULAI Á., ORMOS T., CSÓKÁS J., DRESEN L. 1991: Joint inversion of seismic and geoelectric data recorded in an underground coal mine. Geophysical Prospecting **39**, pp. 643–665

DOBRÓKA M. 1995: Introduction of joint inversion algorithms to the geophysical well logging interpretation. Study, Univ. of Miskolc

DOBRÓKA M., SZABÓ P. N. 2001: The inversion of well log data using Simulated Annealing method. Geosciences, Publications of the University of Miskolc, Series A, Mining **59**, pp. 115–137

GEMAN S., GEMAN D. 1984: Stochastic relaxation, Gibbs distributions, and the Bayesian restoration of images. EEE Trans. Pattern analysis and Machine Intelligence, **6**, 6

METROPOLIS N. 1953: Equation of state calculations by fast computing machines. J. Chem. Phys. **21**, pp. 1087–7092

Mélyfúrási geofizikai adatok globális inverziója

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A nemlineáris mélyfúrási geofizikai inverz probléma megoldására globális optimalizációs módszert mutatunk be. Először lokális válaszegyenleteken alapuló hagyományos mélységpontonkénti (szeparált) inverzióval becsüljük meg a pontbeli kőzetfizikai paraméterek (effektív porozitás, víztelítettség, agyagtartalom, kőzetmátrix fajlagos térfogat) értékeit. Ezután bevezetjük az ún. intervallum inverziós eljárást, mely egy nagyobb mélységintervallum adatrendszerét egyetlen együttes inverziós eljárásban értékeli ki. Az inverziós algoritmusok tesztelése és összehasonlítása céljából szintetikus és terepi adatrendszereket invertálunk. Az inverziós eredmények rámutatnak arra, hogy az intervallum inverzió hatékonysága és a becsült petrofizikai paraméterek pontossága nagyobb, mint lokális pontonkénti inverzió esetén. Az intervallum inverziós módszer igen stabil és megbízható paraméterbecslés tekintetében, és képes meghatározni a rétegvastagságokat, melyek eddig nem szerepeltek ismeretlenként a hagyományos mélyfúrási geofizikai inverzió problémakörében.

ABOUT THE AUTHOR

Péter Norbert Szabó was born in Miskolc in 1976 and attended the Avasi Secondary Grammar School in Miskolc from 1990–1994. He graduated as a geophysical engineer from the University of Miskolc in 1999 after which he participated in the Ph.D. education program on geophysics in the Faculty of Earth Science and Engineering at the University of Miskolc and was awarded his Ph.D. in 2002. He was offered a post as an assistant lecturer in Miskolc University's Department of Geophysics where he has been since January 2003. He is interested in borehole geophysics and geophysical inversion. Since 2002 he has been closely involved in the work of the Association of Hungarian Geophysicists as a member of the Juvenile Delegation. He has taken part in many meetings and conferences both at home and abroad.