ESTIMATION OF THE SUB-SURFACE TEMPERATURE BY MEANS OF MAGNETOTELLURIC SOUNDING

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ABSTRACT

A new method of the temperature estimation in the earth's interior is developed, which is based on using the measurements of magnetotelluric (MT) field at the ground. Basing on the neuronet analysis of MT and temperature data measured at the Bishkek geodynamical testing site in the northern Tien Shan, a feasibility indirect of electromagnetic geothermometer is substantiated. An optimal technique for MT measurements and involvement of temperature logs available is developed. It provides a reduction of the remote temperature estimation errors down to their minimum level. It is shown that the use of 6-8 temperature logs for calibration of electromagnetic data results in 12% relative error of the temperature estimation, whereas availability of prior geological information about the region under study makes it possible to decrease this error furthermore. Practical application of this method will enable one, first, to refine the temperature estimates in cases when the amount of temperature logs available is insufficient; second, to perform more precise temperature prediction in extrapolation mode; third, to monitor the well temperature basing on surface observations of MT field and, at last, to carry out contactless remote temperature estimation in wells with extreme conditions (in particular, typical for supercritical geothermal reservoirs) unsuitable for traditional geothermometers.

INTRODUCTION

Temperature estimation in the Earth's interior is usually based on the borehole temperature logs or on the heat flow data. Meanwhile, both approaches are not free of their own limitations. For example, in the first case a spatial interpolation is required based on the temperature logs that are usually measured in a few wells irregularly distributed over the surface, which often leads to considerable estimation errors. In the second case, construction of temperature model is based on an assumption about a steady state of heat flows at lateral boundaries of the studied domain and as well on prior knowledge of the heat flow (temperature) at the upper and lower boundaries of the area. Since these values (particularly at the lower boundary) are given, as a rule, only very roughly, construction of temperature distribution models on this basis can also be fraught of considerable errors.

Indirect estimates of the sub-surface temperature distribution are often based on geological (Harvey and Browne, 2000; Jansson, Reyr, 2006) or geochemical (Maturgo et al., 2000; Caprai et al., 2006) data. However, these geothermometers often yield erroneous estimates due to using empirical or semi-empirical laws. In the case of using chemical geothermometers the mixing of the deep geothermal fluids with surface waters or their cooling and the associated precipitation/dissolution processes during their rising to the surface are often responsible of the temperature estimation errors (Sanjuan et al., 2006).

It seems most natural to use for these purposes the information about electrical conductivity of rocks because of its direct temperature dependency (Oelsner, 1998). At the same time, complex inhomogeneous structure of the Earth interiors and the lack of information about their properties enables construction of only very coarse temperature models based on the data of global electromagnetic sounding and assumptions as to the conductance mechanisms (Dmitriev et al., 1988).

If several wells with known temperature profiles in the region under study are available, one can suggest an essentially different approach to the estimation of the temperature spatial distribution. This approach is based on the measurements of magnetotelluric (MT) field on the Earth's surface, constructing conductivity profiles from these data and use of neuronet approach for temperature estimation with artificial artificial neural network trained on the correspondence of measured temperature data to calculated conductivity values (Spichak et al., 2006). The purpose of the present work was to verify this approach against the real data and to develop methodological guidelines for its application.

RESEARCH METHODOLOGY

The region of Bishkek geodynamic testing area (BGT) where the measurements were carried out is located in the north of Tien Shan in Chuiskaya depression (Figure 1). In the work, MT data are used measured within a frequency range from 5 x 10^{-4} to 300 Hz in BGT region in the vicinity of 13 wells with known temperature profiles (Duchkov et al., 2001; Schwartzman, 1992).

Vertical conductivity profiles at each site were revealed from dependence of the apparent conductivity determinant on the apparent depth. Figure 2 demonstrates the temperature well logs and resulting conductivity profiles beneath adjacent MT sites.



Figure. 1. Location scheme of MT sites and wells for which temperature data are available.



Figure. 2. The temperature well logs (blue lines) and conductivity profiles beneath adjacent MT sites (red lines).

To study the possibility of temperature estimation in the Earth's crust from MT sounding data, a neuronet approach was applied which had been successfully used earlier for the evaluation of the target macroparameters based on MT data (Spichak and Popova, 2000) and temperature distribution in the Earth's crust from the temperature well logs (Spichak, 2006). The study was performed in three steps: first of all, we estimated the influence of the data volume used for neuronet training on the predicted temperature accuracy; then, influence of training strategy was studied and, finally, the effect of local geological features of the medium was evaluated.

DATA VOLUME EFFECT

To estimate the influence of the training set volume, the neuronets were taught sequentially at 2, 4, 6, 8, 10 and 12 pairs of profiles of temperature and electrical conductivity (hereinafter "T-MT") selected randomly from a whole data volume, and tested on the data obtained at MT sites closest to the wells for which temperature logs were available.



Figure. 3. Average relative error \mathcal{E} (in %) of temperature estimations based on the data electricalal conductivity (blue line) and temperature logs (red line) as a function of the number of pairs (N) of temperature and electricalal conductivity profiles (or temperature logs only) involved in neuronet training

Figure 3 displays relative *rms* errors of the temperature estimation in the well for the case of only temperature data used (red line) and for the case of joint use of electromagnetic data together with temperature logs (blue line). Comparing the plots, one can see that, with an increase in the volume of the training set, if not only the temperature logs but also electromagnetic data are used for temperature estimation, the relative error decreases faster than in the case of only temperature logs used. Besides, yet at a set of 6 T-MT pairs the error becomes practically minimal whereas the estimate based on temperature logs reaches this level when data from 8-10 wells are

used. From this we can draw an important conclusion that given a limited number of borehole temperature measurements, an error of its estimate can be considerably (almost in half) reduced if one uses not only temperature but magnetotelluric data measured on the Earth's surface as well.

EFFECT OF NEURONET EDUCATION STRATEGY

Two strategies were applied to study the influence of local structural features of the Earth's crust between the well MT site, on the error of well temperature estimation based on electromagnetic data. In the first way, the neuronets were trained on five sets of randomly selected 12 T-MT pairs with subsequent forecasting the temperature in three wells (not involved in the training procedure) from the data about electricalal conductivity at closest MT sites. Here, when forecasting the temperature in wells T5 and T6, two variants were considered: (i) using conductivity profiles from sites 627 and 618 and (ii) same from sites 620 and 550. On the other hand, also electromagnetic data at MT sites 618 and 550 were analyzed together with temperature logs measured not only in wells T6 and T1 but also in wells T11 and T14, respectively.

Within the second strategy the neuronet was trained "blindfold" on the whole set of MT data available; then, based on this, electrical conductivity was estimated at depths where the well temperatures were measured and, finally, the neuronet taught on the correspondence between electrical conductivity and temperature in 14 T-MT pairs was used for predicting temperature in the well not involved in training.

In order to compare the results of the temperature estimating based on electromagnetic and temperature data with those obtained with neuronets taught only on temperature data, we trained the neuronets on the same temperature logs that were used as described above (and only on these) and carried out the temperature estimations for the same wells.

The results are shown in Table 1 and Figure 4. Errors of temperature estimation based on the first technique (utilizing electrical conductivity data from the closest MT site) are presented in Table 1 in column marked "1"; estimation errors obtained with the second technique ("blind" use of the whole set of MT data available) are given in column "2" and, lastly, errors of predictions derived from temperature logs only are shown in column "3".

Average relative error of temperature estimation constructed in accordance with the first technique is 11.9%, which turned out an unexpectedly good result for the region of interest, since it shows rather

Table. 1. Errors of well temperature estimation depending on the strategy of neuronet training and on the presence of geological peculiarities in the medium. Estimation errors obtained with the first technique (selective use of MT data) are shown in column labeled "1"; those obtained with the second technique ("blind" use of the whole MT data set available) are shown in column "2", and those obtained from temperature logs alone are shown in column "3".

No. of wells and MT sites	Relative errors of temperature estimates (%)			Local features in the Earth's crust between
	1	2	3	the well and MT site
T1-MT550	24.3	31.3	24.9	Thrust
T4-MT625	12.5	26.1	5.9	No
T5-MT620	7.7	12.4	16.7	Thrust
T5-MT627	0.7	23.8	16.7	No
T6-MT549	8.8	3.9	14.9	No
T6-MT618	16.0	10.5	14.9	No
T7-MT613	0.7	8.9	17.2	No
T8-MT617	1.0	24.4	13.2	No
T9-MT621	8.9	48.1	14.8	No
T10-MT614	1.4	16.1	5.9	No
T11-MT618	29.1	31.7	16.5	No
T12-MT571	9.0	15.6	17.9	No
T13-MT529	9.6	32.1	135.2	Cold meteoritic water flows
T14-MT550	10.2	26.5	27.0	No
T16-MT543	26.9	136.8	101.2	Deep fault
Average error	11.9±2.3	29.9±8.1	29.5±9.2	
Average error, no anomalous zones regarded	8.9±2.5	21.0±3.6	15.0±1.7	



Figure. 4. Measured and modeled distributions of temperature in wells. Black line – measured temperature, red line – temperature model based on the temperature data only, blue line – temperature model based on MT data.

complex geological structure and wide spread of temperature distribution. Average relative error of estimation based on the second approach was 29.9% whereas for the estimation involving sets of temperature logs only it amounted to 29.5%.

Despite the fact that the prediction errors obtained with the second and third training strategies in three cases were lower than those in case of the first technique used, the first approach, on the whole, showed better results in 80% cases. In other words, the best prediction results are provided by conscious reasonable choice of MT sites location closest to the points for which the temperature estimation is carried out.

At the same time, the distance between the T-MT pair used for estimation and MT sites and other wells utilized in neuronet training is not of determinative significance. This is clear from comparison of prediction results in cases of extrapolation observed in wells T7, T9 and T16 located in a marginal part of the studied region. From Table 1 one can see that for the well T16 this error is more than twice as big than the average error, whereas for wells T17 and T9 it is considerably less than the average one. This speaks for the fact that geographical factor plays only secondary part in temperature estimation, which confirms the earlier conclusion made in (Spichak, 2006).

INFLUENCE OF LOCAL GEOLOGICAL IRREGULARITIES

From Table 1 it is apparent that the estimation accuracy is strongly affected by the presence or absence of local geological irregularities between the site where the temperature prediction is made and MT site providing the data for such estimation. Indeed, in case of a well and MT site situated on different sides of a tectonic disjunction (T1-MT550, T5-MT620, T16-MT543), the error of well temperature estimation increased by several times. Similar increase in the prediction error occurred in the presence of local area with thick (about 200 m) Earth's crust layer whereto cool flows penetrate producing anomalous negative temperature gradient with depth (T13-MT529).

In this connection of interest is to compare the estimation results for pairs T1-MT550 and T14-MT550. In the first pair having a thrust between the sites, the distance between the well and the MT site is 2.17 km, and in the second pair the distance is 4.97 km; however, the temperature estimation error here is inversely proportional to the distance. The same effect is observed for pairs T5-MT620 (a thrust is present) and T5-627. It is significant that in both cases the errors of estimation based on the second technique when the data are used "blindfold" show no

correlation neither with the spacing within a T-MT pair nor with an absence or presence of geological peculiarities. Prediction for wells located within "special" regions carried out using neuronets trained on temperature data only, also provides large errors, which is clearly seen from the graphs for pairs T13-MT529 and T16-MT543 (Figure 4).

From this one can conclude that the estimation error depends on the presence of specific geological features in the medium (like thrusts when disjunctive breaks are extending up to the Earth's surface) between the point of temperature estimation and MT site providing the input data for that (although much weaker than in case of second technique applied). Prior knowledge of geological specificity of the region under study can help to find a suitable location of MT observation site with respect to the point where the temperature prediction is carried out and, thus, to reduce significantly the error.

Elimination of the estimates for those T-MT pairs where the Earth's crust contains some geological irregularities reduces the average relative error from 11.9% to 8.9%. Thus, 6-8 temperature logs used for calibration of electromagnetic data turn to be quite sufficient to provide 12% accuracy of the temperature estimate, and in case of prior geological information about the region under study available, 9% accuracy can be attained.

CONCLUSIONS

The studies carried out allow us to make an important conclusion about a possibility of estimating the temperature in the Earth's interior from electromagnetic (magnetotelluric) data measured at the Earth's surface at a set of frequencies. Practical application of this indirect electromagnetic geothermometer will enable one, first, to refine the temperature estimates in cases when the amount of temperature logs available is insufficient; second, to perform more precise temperature prediction in extrapolation mode; third, to monitor the well temperature basing on surface observations of MT field and, at last, to carry out contactless remote temperature estimation in wells with extreme conditions (in particular, typical for supercritical geothermal reservoirs) unsuitable for traditional geothermometers.

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REFERENCES

Caprai, A., Tassi, F. and Vaselli, O. (2006), "Gas geothermometers", *Proc. ENGINE Workshop*, Potsdam, Germany, 20.

Dmitriev, V.I., Rotanova, N.M. and Zakharova, O.K. (1988), "Estimations of temperature distribution in transient layer and lower mantle of the Earth from global magnetovariational sounding data", *Fizika Zemli*, **2**, 3-8 (in Russian).

Duchkov, A.D., Schwartzman, Yu.G. and Sokolova, L.S. (2001), "Tien-Shan deep heat flow: developments and problems". *Geology and Geophysics*, **42**, 10, 1512-1529 (in Russian).

Jansson, K. and Reyr, B. (2006), "Index minerals in defining temperature in potential geothermal reservoirs", *Proc. ENGINE Workshop*, Potsdam, Germany, 21.

Harvey, C. and Browne, P. (2000), "Mixed-layer clays in geothermal systems and their effectiveness as mineral geothermometers", *Proc. World Geothermal Congress*, Kyushu, 1201-1205.

Maturgo, O., Zaide-Delfin, M., Layugan, D. and Catane, J.P. (2000), "Characteristics of the volcanichydrothermal system in Mt. Labo, Philippines: implications to development", *Proc. World Geothermal Congress*, Kyushu, Japan, 1431-1436. Oelsner, C. (1998), "Integrated interpretation of direct and indirect (geoelectricalal) temperature data", *Proc. Int. Conference "The Earth's thermal field and related research methods"*, Moscow, 187-189.

Sanjuan, B., Millot, R. and Brach, M. (2006), "Exploration of potential geothermal reservoirs: use of Na/Li geothermometer and lithium isotopes", *Proc. ENGINE Workshop*, Potsdam, Germany, 17.

Schwartzman, Yu.G. (1992), "Heat field, seismicity and geodynamics of Tien-Shan" (Doctor of Sciences thesis abstract), Bishkek, IGANRK, 38pp.

Spichak, V.V. (2006), "Estimating temperature distributions in geothermal areas using a neuronet approach", *Geothermics*, **35**, 181-197.

Spichak, V.V. and Popova, I.V. (2000), "Artificial neural network inversion of MT - data in terms of 3D earth macro – parameters", *Geophysical Journal International*, **42**, 15-26.

Spichak, V.V., Zakharova, O.K. and Rybin, A.K. (2006), "On the possibility of the indirect electromagnetic geothermometer", *Dokl. Russian Akad. Sci.* (in press).