Proceedings World Geothermal Congress 2010
Bali, Indonesia, 25-29 April 2010

Indirect Electromagnetic Geothermometer: Methodology and Case Study

Viacheslav V. Spichak and Olga K. Zakharova

Geoelectromagnetic Research Centre IPE RAS, 142190, Troitsk, Moscow Region, Russia

spichak@igemi.troitsk.ru

Keywords: geothermometer, electromagnetic sounding, indirect temperature estimation, calibration, artificial neural network

ABSTRACT

Studies were carried out to determine the feasibility of indirect temperature estimation in the Earth's interior from electromagnetic data collected at the surface. Basing on the neuronet analysis of magnetotelluric (MT) and temperature data measured at the Bishkek geodynamical testing ground in northern Tien Shan, optimal methodologies for calibration and application of indirect electromagnetic geothermometers were developed. It is shown that temperature estimation by means of the EM geothermometer calibrated by 6-8 temperature logs results in 12% average relative error (instead of the 30% error achieved using only temperature logs). Availability of prior geological information about the region under study makes it possible to reject inappropriate site locations. This may, in turn, decrease average error by at least 3%.

The results of the electromagnetic temperature extrapolation at depth indicate that the extrapolation accuracy essentially depends on the ratio of the well depth to the extrapolation depth. In particular, when extrapolating to a depth twice as large as the well depth, the relative error is 5-6%, and if the extrapolation depth is three times as large, the error is around 20%. This makes it possible to significantly increase the depth of indirect temperature estimation in the Earth's interior (in particular, for geothermal exploration) based on available temperature logs.

1. INTRODUCTION

Temperature estimation in the Earth's crust is usually based on temperature logs or heat flow gradient data. Actual measured temperature data are limited to the borehole depths amounting in most cases to 1-3 km. Studies of hydrothermal processes showed that specific properties of the underground fluid composition are closely related to the geothermal conditions of their formation. Therefore, studying these properties provides information about the thermal state of the interior that complements the results of direct thermometry and serves as a basis for forecasting the deep geothermal conditions in scantily explored regions.

The temperature dependency of the composition of some characteristic hydrothermal components is established experimentally with so-called indirect geothermometers. Using empirical or semi-empirical formulas, one can roughly estimate the "base depth" temperature from the known amount or proportion of these components in areas of surface manifestations of thermal activity. Researchers frequently use indirect estimates based on geological (Harvey and Browne 1991), geochemical (Kharaka and Mariner 1989) or gas composition (Arnorsson and Gunnlaugsson 1985) data to guess the temperature at characteristic depths.

Despite the fact that the aforementioned indirect geothermometers could serve as useful tools for estimating temperatures at some depths and, thus, for constraining the sub-surface temperature, they can be used neither for constructing the temperature distribution in the studied area nor for its interpolation / extrapolation from the temperature well logs.

Using the electrical conductivity data of rocks seems to be the most natural approach to indirectly estimate temperature, because this property is commonly a function of temperature. Temperature dependence on the electrical conductivity of rocks permits its use for the temperature estimation using well known Archie formula (Archie, 1942). Similar methods can be used accordingly on a regional or even global scale based on empirically matched data (Shankland and Ander, 1983) or data determined from the global magnetovariational sounding (Dmitriev *et al*., 1988). At the same time, the complex, non-homogeneous structure of the Earth and the lack of information about its properties allow construction of only very crude temperature models based on assumptions regarding the electrical conductance mechanisms.

On the other hand, the electromagnetic sounding of geothermal areas (Spichak and Manzella, 2008) may provide indirect temperature estimation in the Earth's interior based on electromagnetic measurements at the surface. Spichak et al. (2007a) recently developed an indirect EM geothermometer, which does not require prior knowledge or guessing regarding the electrical conductance mechanisms in the Earth's crust. In this paper, the proposed method is described and its application to the temperature estimation in the northern Tien Shan area is demonstrated (Spichak et al., 2007a,b; Spichak and Zakharova, 2009).

2. GEOLOGICAL SETTING OF THE STUDIED AREA

The Bishkek geodynamic test site, where EM and temperature measurements were carried out, is located in the Chu Depression in northern Tien Shan, as shown in Figure 1. The Chu depression is an asymmetric structure with gentle northern slopes and steep southern slopes. The Chu monocline, Eastern Chu flexural fracture zone, and Pre-Kyrgyz trough are identified within the Chu basin. Tien Shan is one of the most seismically active regions in the world, and the strongest earthquakes are confined to the northern Tien Shan zone, which is connected to the northern Tien Shan, Kemin and Kungeiskii deep faults.

The groundwater regime is controlled by the regions of surface runoff, the decrement and shallow occurrence of groundwater, and self-outflow of artesian water. Groundwater flow of the pore and pore-fracture circulation types prevails in marginal parts of the Chu basin. Pore water filling in the sequence of Quaternary deposits is the most widespread. These 10–800 m thick deposits include intense low temperature flows of free level groundwater within the alluvial bench and are fed through the percolation of surface and river waters (Zakharova et al., 2007).

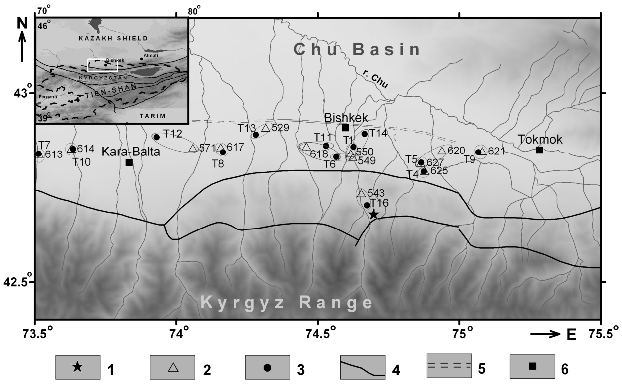

Figure 1: Location of MT sites and wells for which temperature data are available. "MT-site – borehole" pairs used for the EM geothermometer calibration are encircled. 1 – Scientific Station of RAS; 2 – MT sites; 3 – boreholes; 4 – basic faults; 5 – Central – Chu flexure-discontinuity zone; 6 – large cities.

3. EM DATA AND TEMPERATURE LOGS

The MT data were collected in the frequency range from 5 • 10^{-4} to 300 Hz on the sites located in the vicinity of 8 boreholes: T4, T5, T7, T8, T9, T10, T11, T12 (shown in Figure 1). The temperature was measured up to the depths exceeding 1km (Duchkov et al., 2001; Schwartzman, 1992). 1D inversion of the MT data at each observation site was carried out using rotational invariant ("determinant") of the impedance tensor.

The apparent electrical conductivity profiles plotted with the temperature profiles from the nearest boreholes are shown in Figure 2 (Spichak et al., 2007a). In most boreholes in this area, the temperature logs show a nonlinear behavior. It is interesting to note that in some logs, a negative temperature gradient is observed down to depths of about 330 m (wells 1, 13, and 16). The wells used in the present work relate to the regions characterized by either positive or negative temperature gradients (i.e. the cooling action of surface waters extends even down this depth). Such a negative temperature gradient is observed everywhere in the Chu Depression, moving to the north from the Tien-Shan orogene where cool flows are observed at depths of approximately 200 m. The presence of such an effect is explained by the predominance of permeable rocks in the lithological cross-section and by the fact that the wells with anomalous negative temperature gradients are located in the front of the water seepage zone. These waters are mainly supplied by the melting of glaciers.

Strong correlation between electrical conductivity and temperature in most well - MT site pairs can be explained by a depth dependence of the studied parameters typical for layered sedimentary rocks, while weak correlation in some cases is due to the local specificity of the geological medium in the spaces between the wells and corresponding MT sites.

4. CALIBRATION OF THE INDIRECT EM GEOTHERMOMETER

This novel approach is based on temperature estimation by means of the artificial neural network (ANN) calibrated by the correspondence between 1-D electrical conductivity profiles revealed from EM (in particular, magnetotelluric) data collected on the surface in the vicinity of available wells and appropriate temperature logs. In order to estimate the temperature in the area under study, one must obtain the MT data at appropriate sites, provide their inversion and use the indirect geothermometer (i.e. trained ANN) to forecast the temperature profiles in the same locations.

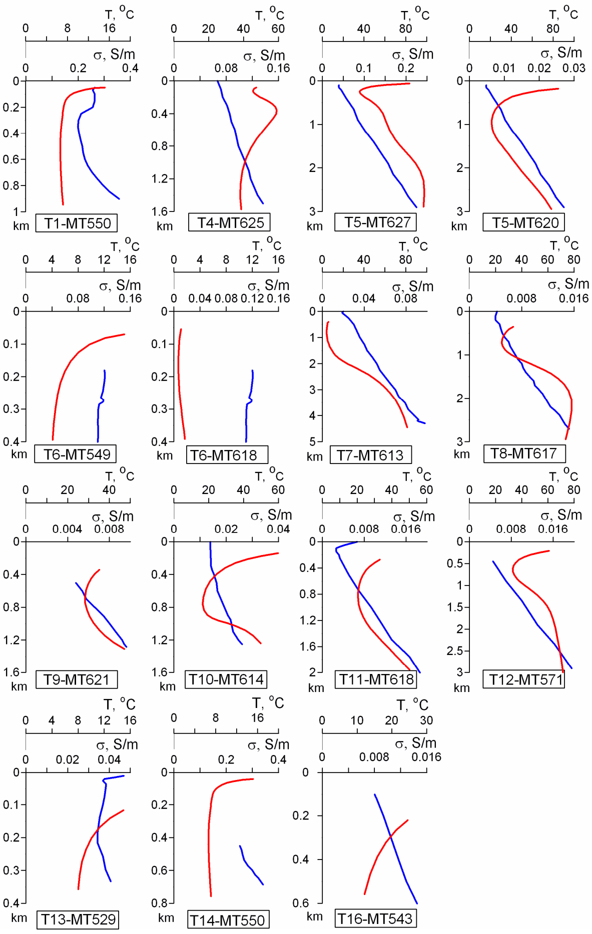

Figure 2: Temperature well logs (blue lines) and electrical conductivity profiles beneath adjacent MT sites (red lines) (Spichak et al., 2007a).

The architecture of an ANN used to this end is as follows: an input layer with 4 neurons (electrical conductivity values determined at the locations of the well temperature records and 3 corresponding coordinates), two hidden layers with 20 and 15 neurons, and an output layer with one neuron (temperature records available at the same space locations). The learning rate (α) was equal to 0.01 and the momentum (β) equal to 0.9. The neural network was taught until it reached a accuracy threshold of 1%. According to experience with the neural network temperature estimation (Spichak 2006), this accuracy threshold is sufficient to achieve 5 to 10% accuracy in the recognition of the target parameters.

In order to assess the quality of the ANN temperature predictions (when the true result is known in advance), the average relative error ε of all testing samples is given by:

$$\varepsilon = \sqrt{\frac{\sum_p (T_{obs,p} - T_{ANN,p})^2}{\sum_p T^2_{obs,p}}} \times 100\% \qquad (1)$$

where p is the number of the temperature measurement ($p=1,\ldots, N_{test}$), N_{test} is the number of temperature records in the well used for testing, and $T_{obs,p}$ and $T_{ANN,p}$ are the observed and estimated temperature values at the p^{th} location.

5. EM TEMPERATURE FORECAST

The studies using ANN were performed in three steps: first, the effect of the data volume used for neuronet training on the forecasting results was estimated; then, the influences of training strategy and prior information were assessed.

5.1 Data volume effect

In order to reveal 1-D electrical conductivity profiles from magnetotelluric data, the Bostick inversion of the impedance "determinant" was used, which is known to be robust with respect to multi-dimensional disturbances (e.g., Park and Livelybrooks, 1989). To estimate the effect of the training sample size, neuronets were successively trained with 2, 4, 6, 8, 10 and 12 pairs of temperature and electrical conductivity profiles (here and after "T-MT") that were randomly selected from the total data set and were tested on data from MT points closest to boreholes for which temperature logs were available. For comparison, the neuronets were alternatively trained using temperature logs alone. The relative *rms* errors of temperature predictions in boreholes are plotted in Figure 3 for the cases of temperature data alone (red line) and electromagnetic data paired with temperature logs (blue line) were used.

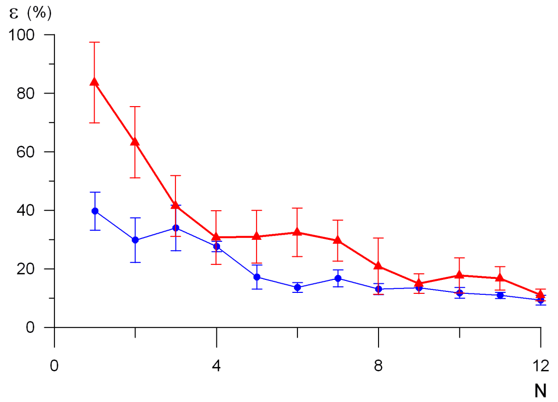

Figure 3: Average relative error $\mathcal{E}$ (%) of temperature estimations based on electricalal conductivity data paired with temperature logs (blue line) and temperature logs alone (red line) as a function of the number of (N) of profiles involved in neuronet training (Spichak et al., 2007a).

Comparison of the graphs shows that, if both temperature and electromagnetic data are used for temperature prediction, an increase in the training sample size decreases the relative error more rapidly than if temperature logs are used alone. Moreover, the prediction error reaches a minimum value for a sample consisting only of six T-MT pairs, whereas the estimation from temperature logs attains the same level with the use of data of eight to ten boreholes. The important implication of this is that if borehole measurements of temperature are limited, the temperature prediction error can be substantially reduced (by nearly two times) by using both temperature and MT data.

5.2 Effect of the neuronet training strategy

To examine effect of the neuronet training strategy on the error of temperature prediction in the borehole from electromagnetic data, two strategies were used. In the first case, neuronets were trained with five samples of 12 randomly selected T-MT pairs, and the temperatures in three boreholes whose data were not used for training were then predicted from the electrical conductivity data of the nearest MT points. The temperatures in boreholes T5 and T6 were predicted separately for the conductivity profiles from sites 627 and 618 (T5) and from sites 620 and 549 (T6). In contrast, the electromagnetic data at MT sites 618 and 550 were analyzed together with temperature profiles measured not only in boreholes T6 and T1, but also in T11 and T14, respectively.

In the framework of the second strategy, the neuronet was trained with all available MT data, after which this neuronet was used for predicting the conductivity at the depths of borehole temperature measurements. Finally, the neuronet trained on the basis of the correspondence between conductivity and temperature in 14 T-MT pairs was used to predict the temperature in a borehole whose data were not used for training. In order to compare the results of temperature prediction based on electromagnetic and geothermal data with results obtained by means of neuronets trained with temperature data alone, neuronets were trained only with the same temperature logs, and the temperatures in the same boreholes were predicted.

The predicted results are presented in the Figure 4 and Table 1.

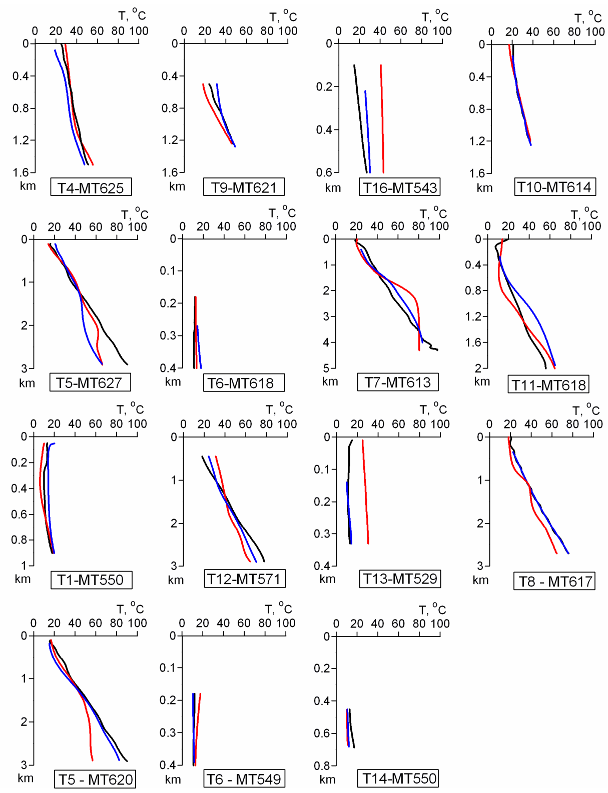

Figure 4. Measured and modeled distributions of temperatures in wells. Black line – measured temperature, red line – temperature model based on the temperature data only, blue line – temperature model based on MT and temperature data (Spichak et al., 2007a).

Table 1. Errors of well temperature estimation depending on the strategy of neuronet training.

Nos. of wells and MT sites	Relative errors of temperature estimates (%)			Local features in the Earth's crust between the well and MT site
	1	2	3	
T1-MT550	24.3	31.3	24.9	Overlapped fault
T4-MT625	12.5	26.1	5.9	No
T5-MT620	7.7	12.4	16.7	Overlapped fault
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 meteoric 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 when prior geological information is taken into account	8.9±2.5	21.0±3.6	15.0±1.7	

The uncertainties of the temperature prediction by the first and second methods (the use of electrical conductivity data from the nearest MT point and the "blind" use of all available MT data) are given in columns 1 and 2 of the Table 1, respectively. The uncertainties of the ANN prediction from the third method (temperature logs alone) are given in column 3.

The average relative error of the temperature prediction evaluated by the first technique was 11.9%, which is an unexpectedly good result for this region, which is characterized by a complex geological structure and a large scattering of temperature distributions (Zakharova et al., 2007). The average relative errors of prediction by the second and third methods were 29.9% and 29.5%, respectively. Although the prediction errors of the second and third techniques were in three cases smaller than those of the first one, the results predicted by the first technique were better in 80% of the cases.

In other words, a reasonable choice of the configuration of MT points nearest to points at which the temperature is to be predicted yields the best results of prediction. However, the distance of the predicted T-MT pair from the MT points and the remaining boreholes whose data were used for training the neuronet is not a decisive factor. This is evident from the comparison of prediction results obtained by extrapolation to boreholes T7, T9, and T16, which were located on the periphery of the region studied. The Table 1 shows that the error for borehole T16 is two times larger than the average error, whereas the T7 and T9 errors are substantially smaller than the average error. This fact indicates that the geographic factor is only of secondary importance for the temperature estimation, confirming the conclusion made by Spichak (2006).

5.3 Effect of prior geological information

It can be seen in the Table 1 that the presence of local geological heterogeneities between a point at which the temperature is estimated and an MT site whose data are used for this assessment has a significant effect on the prediction errors. In particular, when the borehole and the MT site were located on opposite sides of thrust or deep tectonic faults (pairs T1-MT550 and T16-MT543, accordingly) revealed from prior geological survey (Mikolaichuk, 1999), the errors of temperature estimation for the borehole increased by several times. A similar increase in the estimation error was observed in boreholes T6 and T13 in the presence of a local zone with a thick (about 200 m) crust layer penetrated by flows of cold water that formed an anomalous negative vertical temperature gradient (Lesik, private communication).

In this connection, it is interesting to compare the estimation results for the pairs Tl-MT550 and T14-MT550. The T-MT spacing is 2.17 km for the first pair, characterized by the presence of a fault between the borehole and the MT site, and 4.97 km for the second pair. However, the temperature estimation error in this case was found to be inversely proportional to the spacing. It is interesting that the prediction errors of the second technique (using all available MT data) are insensitive to both the T-MT pair spacing and the presence of a fault. The application of neuronets trained with temperature data alone to the temperature estimation for boreholes located in geologically complex zones also yields large errors, as can clearly be seen in the plots for the pairs T13-MT529 and T16-MT543 shown in Figure 4).

This suggests that estimation errors associated with this method depend on the presence of specific geological features (of the thrust type if disjunctive disturbances are traceable on the surface) between the temperature estimation point and the MT site whose data are used for the estimation. However, this dependence is substantially weaker than in the cases of application of the two other approaches.

Thus, prior knowledge of the geological structure of the region under study can help to correctly locate the MT sites with respect to the point where the temperature is predicted and thereby reduce the estimation errors. In particular, elimination of pairs T1-MT550 and T16-MT543 located in laterally non-homogeneous zones reduced the average relative error of the temperature estimation from 11.9% to 8.9%.

Thus, six to eight temperature logs used for calibration of electromagnetic data were sufficient to ensure a 12% accuracy of temperature prediction. If prior geological information about the region under study is available from geological survey or prior analysis of the available MT data, this accuracy can be improved to 9%. It is worth mentioning that under favorable geological conditions (lateral homogeneity between the MT sites and areas where the temperature is to be estimated, as well as absence of cold meteoric water flows in the latter zones disturbing regular temperature profiles and so on), the average temperature estimation error could be reduced to 6%.

Another important inference is that prior knowledge of geological features of the region under study more significantly improve temperature estimates obtained from the temperature logs only (from 29.5% to 24.4%) than those obtained by indirect electromagnetic geothermometers (from 11.9% to 8.9%). This indicates that the effect of lacking prior knowledge of the geology on the accuracy of temperature reconstruction based on a routine approach is more negative than in case of the temperature prognosis using the new technique. In other words, temperature estimates using an indirect EM geothermometer are more resistant to geological noise than those obtained using the temperature logs alone, and thus are more robust.

6. EM TEMPERATURE EXTRAPOLATION IN DEPTH

It is often necessary to estimate the temperature distribution in geothermal reservoirs lying at depths that exceed the depths of the drilled wells. Spichak and Zakharova (2009) studied the feasibility of the application of indirect EM geothermometer to EM temperature extrapolation with depth. The results obtained for the northern Tien Shan area following this paper are discussed below.

6.1 Geothermometer calibration

At the stage of the thermometer calibration, the artificial neuronets were taught by correspondence between the values of measured temperature and electrical conductivity estimated from MT data at a neighboring site (such T-MT pairs are circled in Figure 1). The depth of each well was divided into 10 intervals, and the training was carried out successively at the shallower intervals. After the training, the neuronets were tested at the remaining (deeper) parts of temperature profiles, the data from which were not used for training.

6.2 Temperature extrapolation

The errors of well temperature estimation at different depths depending on the portion δ of temperature profiles and electrical conductivity (from the surface to maximum well depths) used for neuronet calibration are shown in Table 2. It can be seen in the Table that for all boreholes, the relative testing errors ε decreased monotonically with increasing δ (on average: from 52.4 % at $\delta = 0.1$ to 2.4% at $\delta = 0.9$). Yet starting from $\delta = 0.5$, the errors ε of extrapolation with depth become, on average, lower than 10%, although this level is achieved at different values of δ for different wells.

In Figure 5, a graph is shown illustrating the dependence of the mean relative error ε of the neuronet prognosis (extrapolation) of temperature with depth (based on electromagnetic data measured at the MT site closest to the well) on the portion of the electrical conductivity and temperature profiles used for the neuronet training. From this graph, one can conclude that to reach a 5-6% error, it is quite sufficient to use only the temperature and electrical conductivity data for the upper half of the profile for ANN training. In other words, the application of indirect electromagnetic geothermometers could enable obtaining high-accuracy temperature estimates at depths twice as large as the depths of the drilled wells for which the temperature data are available.

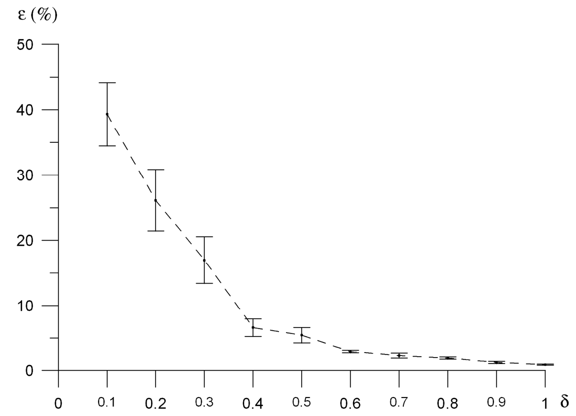

Figure 5. Dependence of the average relative error ε of the EM temperature extrapolation on the portion δ of the temperature well logs used for the neuronet training (Spichak and Zakharova, 2009).

Predicted and actual temperature values in 8 wells are plotted in Figure 6. Based on the above results, the extrapolation was confined to the lower half of depths for all temperature profiles. As can be seen in Figure 6, the predicted curves insignificantly depart from the actual ones only in 3 of 8 cases. Moreover, the departure was observed at depths from 2.5 to 4.5 km in only two cases (T7-MT613 and T12-MT571).

Table 3 shows the temperature estimation errors for all 8 boreholes in the case where the temperature in the bottom halves of the boreholes was estimated by means of the EM geothermometer and by ANN extrapolation using only the temperature records in the upper halves (provided according to the technique proposed in (Spichak, 2006)). In the former case, the average error is 5.8%, while in the latter case, it is 27.4%. It is worth mentioning that routine temperature extrapolation based on the MATLAB library results in constant temperature values with depth.

CONCLUSIONS

The studies carried out using unique temperature and MT data sets allow us to make an important conclusion about a possibility of estimating the temperature in the Earth's interior from electromagnetic (in particular, magnetotelluric) data measured on the surface. In contrast with known indirect geothermometers, which attribute the temperature dependency of the composition of some characteristic hydrothermal components observed at the surface to the supposed depth of their origin, the electromagnetic method provides the spatial temperature distribution in the earth in the absence of manifestations of geothermal activity on the surface.

It is important to note that the temperature estimates obtained with indirect EM geothermometers are based on its advance calibration of electrical conductivity - temperature relationships in a few wells. Thus, these estimates do not depend explicitly on alteration mineralogy or other factors. Indirect EM geothermometers provide more accurate temperature estimations than those obtained using any interpolation method of the temperature well logs and are more robust in the absence of prior geological information (i.e. smaller error results from a lack of this information).

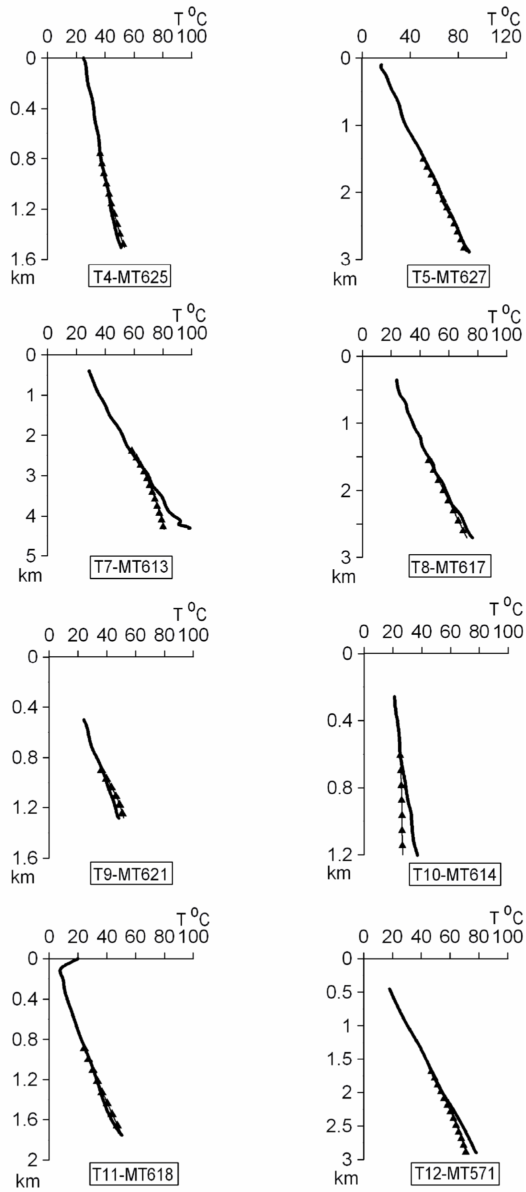

Figure 6. Well logs (solid lines) and estimated temperature profiles (lines with triangles) obtained by extrapolation on the lower half of the profile using the ANN trained on the correspondence between the electrical conductivity and temperature at the points belonging to the upper half of the profile (Spichak and Zakharova, 2009).

The application of the indirect electromagnetic geothermometers allows high accuracy temperature estimation at depths exceeding the depths of drilled wells for which temperature data are available. For example, in extrapolation to a depth twice as large as the well depth, the relative error is 5-6%, and in case of its threefold excess, the error is about 20%. This result makes it possible to significantly increase the depth of the indirect temperature estimation in the Earth’s interior (in particular, for geothermal exploration) based on the available temperature logs in wells, which are often insufficiently deep.

Thus, practical usage of indirect EM geothermometers has four main benefits. First, it enables the estimation of the sub-surface temperature distribution in cases when the number of available temperature logs is insufficient. Second, it allows researchers to perform more precise temperature estimations from extrapolation. Third, it enables the monitoring of temperature with depth based on surface observations of MT field. Finally, it allows remote temperature estimations in geothermal wells with extreme conditions unsuitable for traditional geothermometers as well as in productive wells without disturbing the production process.

ACKNOWLEDGMENTS

The authors acknowledge Dr. A. Rybin, who provided the temperature data measured in the northern Tien Shan area. This work was supported by the INTAS (project no. 03-51-3327) and the Russian Foundation for Basic Research (project no. 07-05-00017).

Table 2. Errors of temperature extrapolation with depth depending on the portion δ of the temperature well logs and electrical conductivity profiles at adjacent MT sites used for the neuronet training.

δ	T4/ MT625	T5/ MT627	T7/ MT613	T8/ MT617	T9/ MT621	T10/ MT614	T11/ MT618	T12/ MT739
0.1	32.8	67.4	65.5	55.5	33.4	27.3	73.5	63.8
0.2	8.2	36.9	63.3	56.1	34.6	27.3	64.0	24.9
0.3	7.2	12.5	54.2	3.2	37.4	27.5	47.2	24.5
0.4	4.7	5.5	17.2	3.8	1.5	18.3	24.8	8.8
0.5	3.2	1.5	6.8	2.7	6.0	14.0	7.9	4.5
0.6	2.8	2.9	8.4	5.0	2.2	5.0	8.5	5.7
0.7	2.6	2.0	2.3	1.3	1.9	8.3	8.7	4.9
0.8	2.4	4.0	1.8	1.9	2.9	4.1	6.6	1.3
0.9	1.2	1.9	1.4	1.5	0.8	2.3	5.8	1.6

Table 3. Temperature estimation errors (%) depending on the extrapolation technique used: ε corresponds to indirect EM geothermometer extrapolation, while ε* relates to ANN temperature extrapolation using only the temperature records.

Well	MT site	T-MT spacing (km)	ε (%)	ε* (%)
T4	MT625	0.42	3.2	20.0
T5	MT627	0.18	1.5	31.1
T7	MT613	0.24	6.8	28.4
T8	MT617	1.74	2.7	25.3
T9	MT621	1.32	6.0	25.5
T10	MT614	0.21	14.0	22.0
T11	MT618	4.95	7.9	34.0
T12	MT571	8.41	4.5	32.9
Average			5.8±1.3	27.4±1.7

REFERENCES

Archie, G.E.: The electrical resistivity log as an aid in determining some reservoir characteristics. *Tran. AIME* **146**, (1942), 54-67.

Arnorsson, S., and Gunnlaugsson, E.: New gas geothermometers for geothermal exploration-calibration and application, *Geochimica et Cosmochimica Acta*, **49**(6), (1985), 1307-1325.

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

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

Harvey, C.C., and Browne, P.R.L.: Mixed-layer clay geothermometry in the Wairakei geothermal field, New Zealand, *Clay and Clay Minerals*, **39**, (1991), 614-621.

Kharaka, Y.K., and Mariner, R.H.: Chemical geothermometers and their application to formation waters from sedimentary basins, *Thermal History of Sedimentary Basins* (Ed. N.D. Naeser and T. McCulloch), S.C.P.M. special issue, Springer Verlag, (1989), 99-117.

Mikolaichuk, A.V.: Modern faults of the Kyrgiz range. *Science and New Technologies*, **2**, (1999), 42-47 (in Russian).

Park, S.K., and Livelybrooks, D.W.: Quantitative interpretation of rotationally invariant parameters in magnetotellurics, *Geophysics*, **54** (11), (1989), 1483-1490.

Schwartzman, Yu.G.: Heat flow, seismicity and geodynamics of Tien-Shan. *Doctor of Sciences thesis abstract*, Bishkek, IGANRK, (1992), 38 (in Russian).

Shankland, T., and Ander, M.: Electrical conductivity, temperatures, and fluids in the lower crust, *J. Geophys. Res.* **88**(B11), (1983), 9475-9484.

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

Spichak, V., and Manzella, A.: Electromagnetic sounding of geothermal zones, *Journal of Appl. Geophysics*, (2009), doi:10.1016/j.jappgeo.2008.05.007.

Spichak, V., and Zakharova, O.: The application of an indirect electromagnetic geothermometer to temperature extrapolation in depth, *Geophysical Prospecting*, 57, (2009), 653-664.

Spichak, V.V., Zakharova, O.K., and Rybin, A.K.: On the possibility of realization of contact-free electromagnetic geothermometer, *Dokl. Russian Academy of Sci.* **417A**(9), (2007a), 1370-1374.

Spichak, V.V., Zakharova, O.K., and Rybin, A.K.: Estimation of the sub-surface temperature by means of magnetotelluric sounding, *Proceedings*, XXXII Workshop on Geothermal Reservoir Engineering, Stanford University, Stanford, CA (2007b).

Zakharova, O.K., Spichak, V.V., Rybin, A.K., Batalev, V.Yu., and Goidina, A.G.: Estimation of the correlation between the magnetotelluric and geothermal data in the Bishkek geodynamic research area, *Izvestya, Physics of the Solid Earth*, **43**(4), (2007), 297-303.