Development of a Neural Network System for Geothermal Resource Assessment

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ABSTRACT

To evaluate geothermal resource, we developed a neural network system that estimates the underground temperature from surface surveys data. This system showed that neural networks can be utilized fully for geothermal resource assessment, using appropriate processing and selection of input and output data. Furthermore, the sensitivity analysis was performed using this proposed system. The influence of some of ground surface survey items on the underground temperature is examined.

1. INTRODUCTION

The neural network system(Farlman et al(1983), Hopfield(1982), and Rosenblatt(1958)) is an information processing system modeled on the human nervous system. As is well known, this system has great capabilities in the field of pattern recognition and classification. The neural network system is characterized by: (1) being able to evaluate a large volume of data in a short period of time, (2) being useful for equivocal data, and (3) being able to self-teach when proper data is provided. Yasuda et al (1993,1994) already applied it to assessment of determination on concrete structure. In geothermal energy development, geothermal resource is evaluated according to judgments based on empirical knowledge, by using multiple survey data items. Features of the neural network system are therefore compatible with the capabilities required for geothermal resource assessment.

In order to examine the application of a neural network to geothermal resource assessment in this study, we developed a system that assess the underground temperature from the results of ground surface surveys, using a neural network. Additionally, we used this system to investigate the sensitivity of the underground temperature to ground surface survey results.

2. OUTLINE OF GEOTHERMAL RESOURCE ASSESSMENT

In geothermal energy development, it is necessary to evaluate an underground geothermal resource from the results of ground surface surveys. The New Energy and Industrial Technology Development Organization (NEDO) has undertaken the geothermal development promotion survey in Japan (NEDO(1983–1992)), in which ground surface data from geological, geochemical and geophysical surveys are obtained. Above with these surveys,several wells of about 1000 – 1500 meters depth have been drilled in each area to know the underground geology and temperature. In this study, an investigation was made as to whether underground temperature can be assessed from results of these ground surface surveys.

Among the ground surface survey results, some 25 input items were selected which are frequently used usually, as listed in Table 1. The nine input items on which numbers are half-tone screened

1	Geology	14	Temperature of hot spring rater
2	Rock facies	15	pH of hot spring water
3	Distance from the nearest fault		Hot spring rater types based on the most dominated anion
4	Distance from the nearest active volcano	17	Cl composition of hor spring water
5	Age of volcanic activity	18	Underground temperature estimated by using chemical geothermometer
6	Distance from the nearest hydrothermal alteratinn halo	19	Anion index (AI) $AI=0.5[SO_4/(Cl+SO_4)+(Cl+SO_4)/(Cl+SO_4+HCO_3)]$ (unit:equivalents)
7	Area of hydrothermal alteration halo	20	Resistivity in the shallow layer
	Hydrothermal alteration halo types based on the chemical character	21	Resistivity in the intermediate layer
9	Hydrothermal alteration halo types based on mineral paragenesis	22	Resistivity in the deep layer
10	Gas constituent of Hg	23	Distance from the nearest-fault estimated by using resistivity survey results
11	Gas constituent of CO_2	24	Bouguer anomaly
12			

Table 2 Classification of temperature and coresponding number of wells

Output item	Output classification					
Underground temperature(℃)	300	250 300	200 250	150 200	100 150	< 100
(Symbol)	(Ⅰ)	(Ⅱ)	(Ⅲ)	(Ⅳ)	(Ⅴ)	(Ⅵ)
Number of wells	2	12	16	27	45	47

Figure 1 Location of geothermal development promotion survey areas

are discontinuous hierarchical data. The remaining 16 input items are continuous numeric data. **An** anion index, **AI,** which **is** listed in No. 19 of Table 1 **is** an indicator to estimate the proximity to the center of geothermal activity **proposed** by Noda(1987). The output item is the underground temperature, which is classified into **six** ranges as listed **in** Tahle 2. **The** temperature in Tahle 2 **is** to **he** compared to the maximum temperature ohtained in a given well. The number of wells classified by **six** ranges of temperature **is** also listed in this table.

The data for 24 **areas** shown in Figure 1 are available for all 25 items listed in Tahle 1.

The **data used** in this **study** includes that for the 149 wells in these 24 **areas.** **We** have taken the NEDO ground **surface** survey **results as** the input values for the neural **network** for each area. The numher of wells drilled in each area is **as** listed in Table 3. Because of all **wells were** drilled **at** geothermal areas, most of them are thought to have been drilled into a hydrothermal system of which temperature shows various value **at** each **well.** In each well, the temperature changes with depth in a well drilled in hydrothermal **system** is usually very small as the vertical temperature distribution in a hydrothermal system is smoothed by thermal convection. Depending on such a consideration. the differences of drilled depths among wells, 1000 – 1500 meters as described above, are thought not to be important in this **study.** The maximum temperature in each well **is** the neural network **output.** The symbols (＊ and ＃) in this table indicate which data is used for learning and which data is used for verification, as described kiter.

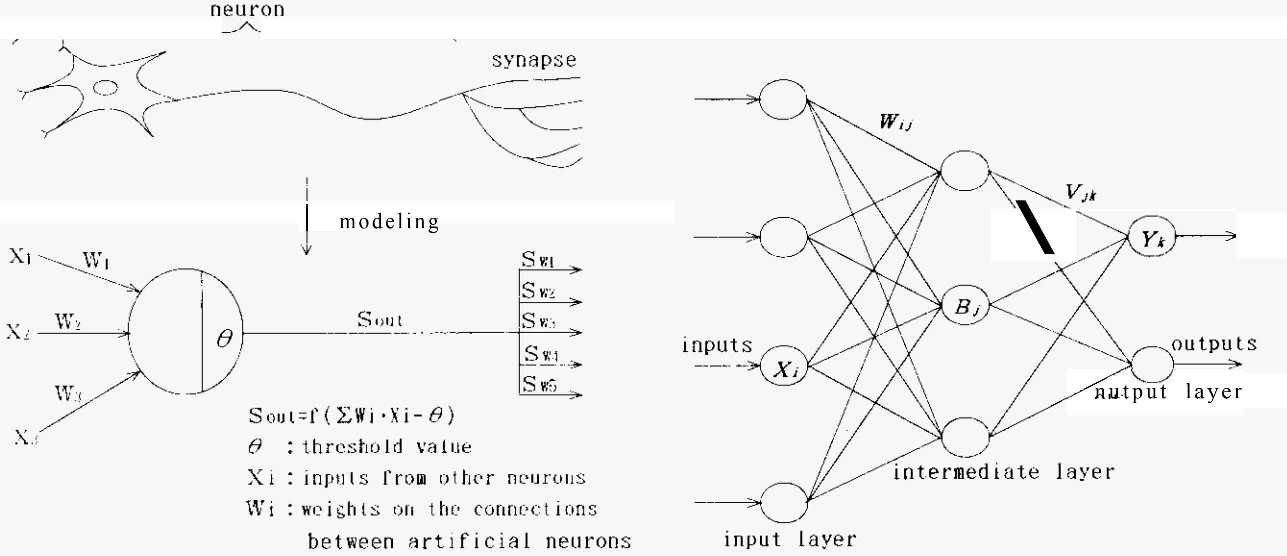
3. OUTLINE OF NEURAL NETWORK SYSTEM

The neural network system differs significantly from statistical methods such as multi-variate analysis, in that the pattern recognition capability of the system is improved hy learning. A well-debugged program **is** indispensable to conventional computer software. **Likewise,** a neural network also requires enough learning data that has hcen examined completely. The hierarchial neural network used in this **study,** shown in **Figure** 2, **is** the combination of a large numher of cells modeled on a neuron (nerve cell). The hierarchial structure consists of the input layer. the output layer, and the intermediate **layers** installed between the input and output layers.

The neurons in each layer are connected by an element called

Table 3 Geothermal development promotion survey areas used for system creation, and number of wells

No.	Area name	Wells	No.	Area name	Wells	No.	Area name	Wells
1	Kamikawa	7	9	Okiura	5	17	Okuaizu	7
2 *	Teshikaga seibu	6	10 #	Tazawa lake tobu	8	18 #	Outaki	4
3	Akan	7	11	Yuda	6	19	Oitagawa joryu	3
4	Toyoha	7	12 #	Minase	7	20	Kuju	7
5 *	Iburi	6	13	Yuzawa ogachi	7	21 *	Kurino•Tearai	7
6	Yakumo	7	14 #	Mogami Akakura	4	22	Unzen seibu	7
7 *	Minamikayabe	7	15	Azuma hokubu	5	23	Hishikari	7
8	Shimokita	6	16	Inawashiro	6	24	Ikeda lake shuhen	6
							Total number of wells	149



(a) Modeling of neurons (b) Hierarchial structure of neurons

Figure 2 Hierarchial structure of neural network

a synapse, and the stimulus of the neuron (input signal) is sent sequentially from the input layer to the output layer. The stimulus intensity (signal level) varies depending on a threshold value and weights set between the neuron and synapse. In this study, the sigmoid function given in equation (1) is used as the general model indicating the response characteristic of the stimulus intensity. Therefore, the output value from each cell is a real number between 0 and 1. The output value of a cell in the output layer is called a certainty value.

$$f(u_i) = \frac{1}{1 + exp(-u_i / T)} \quad \cdots\cdots\cdots\cdots \quad (1)$$

where, $u_i = \Sigma W_i \times X_i - \theta$

$f(u_i)$: output stimulus intensity

X_i : input stimulus value

W_i : weight

θ : threshold value

T : constant

As the constant T in equation (1) rises, the sigmoid curve of the sigmoid function becomes more gradual. As T drops, the sigmoid curve becomes sharper. Generally speaking, the learning speed of the neural network is fast if T is set at a low level. In contrast, the precision of recognition of an unlearned pattern tends to deteriorate in this case. Determining an effective value of T is a subject which remains to be pursued in the future. Judging on past experience, T in this study was set at 1.0 (T=1.0).

The learning method of the neural network used in this study is called the back propagation method. As described previously, the input data varies with the threshold value and weights while it is sent from the input layer through the neuron and synapse network. The resultant data is output to each cell of the output layer as a certainty value. Moreover, the correct answer value, called the teacher value, is also sent to each cell of the output layer. In order to reduce the error between the certainty value and the teacher value, an adjustment of the threshold value and weights are propagated back from the output layer to the input layer. This is called the back propagation method.

4. GEOTHERMAL RESOURCE ASSESSMENT SYSTEM USING NEURAL NETWORKS

Among the 24 areas listed in Table 3, 20 areas were used for system learning. The remaining four areas were used for verification of the system in which learning was completed.

4.1 Neural network systems

Three neural network systems were developed in this study, as listed in Table 4. In system No.1, the 20 areas except the four *-marked areas were selected for learning areas and the 10 numeric data items shown in Table 1 were input as direct values. In system No.2, learning areas were the same as for system No.1. However, the 16 numeric data items are input as a rank value from 1 to 6. In system No.3, the numeric data were input in the same way as for system No.1. However, the 20 areas except the four #-marked

Table 4 Learning condition and learning results

System No.	Learning condition: Numeric data input format	Learning condition: Learning area	Learning results: No. of learned wells	Learning results: No. of correct answer wells	Learning results: Recognition rate (%)
1	Direct value	20 areas except * marked areas	126	122	96.8
2	Rank value	20 areas except * marked areas	126	125	99.2
3	Direct value	20 areas except # marked areas	123	107	87.0

areas were selected for learning areas.

There are 25 cells in each input layer, corresponding to the number of input items listed in Table 1, and six cells in each output layer, corresponding to the temperature ranges listed in Table 2. The number of intermediate layers and the number of cells chosen involves trade-offs between learning speed and recognition capability. Therefore, 2 layers × 25 cells were selected as the minimum number for complete recognition capability, based on pre-examination trial results.

4.2 Learning results of systems

Learning was repeated as to 30,000 times until all certainty values for the correct answer cell in the output layer were more than 0.9. The percentage of correct answers after all learning is completed is defined as the recognition rate. The learning result is listed in Table 4. The recognition rate of all systems is about 90%. This shows that a system with a high recognition rate has been developed through the learning process.

4.3 Verification results of systems

Verification results of the system are listed in Table 5 and Table 6. In addition to the temperature classification in which there are six cells as temperature ranges in the output layer (described previously), three output cells as temperature ranges were also applied. The three cells of the latter classification are > 200℃, 150 – 200℃, and < 150℃, corresponding to steam power generation, binary power generation, and direct utilization respectively. In Tables 5 and 6, the Roman numerals shown in the correct-answer and system-output columns indicate the temperature ranges listed in Table 2. The correct answer is the measured maximum temperature in each well. The system output is the output temperature range obtained by a neural network system in which learning has been completed. The cell that displays the highest certainty value among the six output cells was defined as the system answer. The mark "○" shown in the system-judgment column indicates that a correct answer has been obtained in the temperature classification in which there are six cells as temperature ranges in the output layer. The mark "△" indicates that a correct answer has been obtained in the classification of three temperature ranges. In this classification, the temperature ranges of Ⅰ, Ⅱ and Ⅲ become a range of > 200°C and the temperature ranges of Ⅴ and Ⅵ become also a range of < 150°C as described before. Consequently, the correct answer rate by this classification should be improved better than by the classification of six ranges. The mark "×" indicates that an incorrect answer has been obtained in the classification of three ranges. The correct answer rate is the percentage of marks "○" or "△" for all the verified data. System No.1 and No.3 have a high correct answer rate, from 50 – 70%. There are not much differences in the correct answer rates between these two systems. But system No.2 has a low correct answer rate, of which reason is

Table 5 Verification results system

No.	Correct answer	System No. 1 Output	System No. 1 Judgment	System No. 2 Output	System No. 2 Judgment
1	Ⅱ	Ⅴ	×	Ⅴ	×
2	Ⅱ	Ⅵ	×	Ⅳ	×
3	Ⅱ	Ⅵ	■	Ⅴ	×
4	Ⅲ	Ⅴ	×	Ⅳ	×
5	Ⅳ	Ⅱ	×	Ⅳ	○
6	Ⅳ	Ⅳ	○	Ⅳ	○
7	Ⅳ	N	3	Ⅳ	○
8	Ⅴ	Ⅵ	△	Ⅳ	×
9	Ⅴ	Ⅵ	△	Ⅳ	×
10	Ⅴ	Ⅳ	×	Ⅳ	×
11	Ⅴ	Ⅵ	△	Ⅳ	×
12	Ⅵ	Ⅵ	○	Ⅵ	○
13	Ⅵ	Ⅵ	○	Ⅵ	○
14	Ⅵ	Ⅵ	○	Ⅳ	×
15	Ⅵ	Ⅲ	×	Ⅲ	×
16	Ⅵ	Ⅵ	○	Ⅵ	○
17	Ⅵ	Ⅵ	○	Ⅵ	○
18	Ⅵ	Ⅵ	○	Ⅴ	△
19	IT	Ⅵ	○	Ⅴ	△
20	Ⅵ	Ⅵ	○	Ⅴ	△
21	Ⅵ	Ⅵ	○	Ⅳ	[illegible]
22	Ⅵ	Ⅵ	○	Ⅴ	[illegible]
23	Ⅵ	Ⅵ	○	Ⅴ	[illegible]
Correct answer rate (%)	Only mark "○" is correct		56.5		30.4
	Mark "△" is also correct		69.6		52.2

Table 6 Verification results of system

No.	Correct answer	System No 3 Output	System No 3 Judgment
1	Ⅱ	Ⅳ	×
2	Ⅱ	Ⅲ	△
3	Ⅲ	Ⅳ	×
4	Ⅳ	Ⅱ	×
5	Ⅳ	Ⅳ	○
6	Ⅳ	Ⅴ	×
7	Ⅳ	Ⅴ	×
8	Ⅳ	Ⅴ	×
9	Ⅳ	Ⅴ	×
10	Ⅴ	Ⅴ	○
11	Ⅴ	Ⅴ	○
12	Ⅴ	Ⅴ	○
13	Ⅴ	Ⅴ	○
11	Ⅴ	Ⅵ	△
15	Ⅴ	Ⅳ	×
16	Ⅴ	Ⅵ	△
17	Ⅴ	Ⅴ	○
18	Ⅴ	Ⅴ	○
19	Ⅴ	Ⅴ	○
20	Ⅵ	Ⅲ	×
21	Ⅵ	Ⅵ	○
22	Ⅵ	Ⅵ	○
23	Ⅵ	Ⅵ	○
24	Ⅵ	Ⅴ	△
25	Ⅵ	Ⅵ	○
	Ⅵ	Ⅵ	○
Correct answer rate (%)	Only mark "○" is correct		50.0
	Mark "△" is also correct		65.4

thought to be derived from a difficulty to distinguish the difference in a subtle pattern when the input data is set as a rank value.

When a judgement is compared for different temperature range, the rate of "^" in the high temperature wells those shown in the line of younger number of Table 5 and 6 is more in all systems. The reason probably that there were not much high-temperature wells included among the data as shown previously in Table 2, comparing for lower-temperature wells as a whole, so that information on this range could not be learned completely.

5. SENSITIVITY ANALYSIS

The influence of the input items on the output items was studied so as to quantitatively know the correlation between ground surface survey items and underground temperature, and compare the correlation with the empirical rules.

The amount that a change in the value "X_i" of an input item "i" influences the value "Y_k" of an output item "k" is defined by partial differentiation. Since an intermediate layer exists in the system in this study, the value "B_j" of cell "j" in the intermediate layer and the value "Y_k" of output item "k" shown in Figure 2, are each given by the following equations, according to equation (1).

$$Y_k = f\left(\sum V_{jk} \cdot B_j - \theta_k\right) \quad (2)$$

$$B_j = f\left(\sum W_{ij} \cdot X_i - \theta_j\right) \quad (3)$$

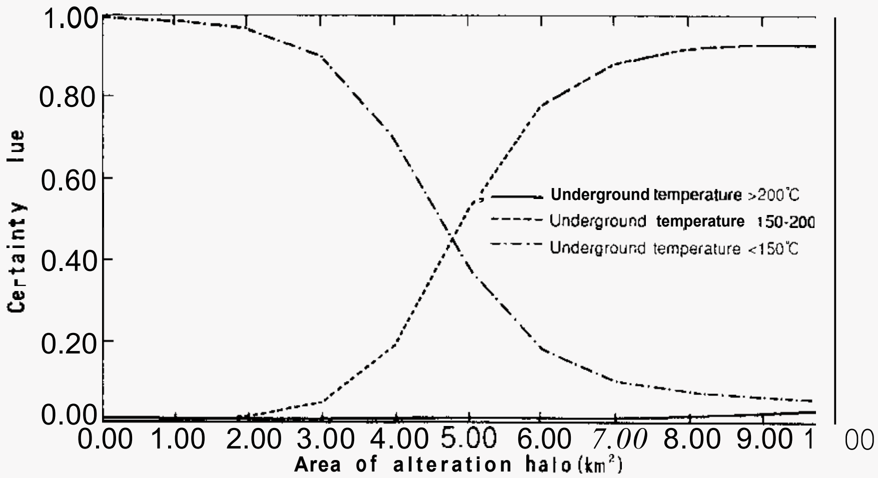
Assume that input item values other than "X_i" are constant in this case. The sensitivity of "Y_k" to "X_i" is given by equation (4) according to equation (2) and (3).

$$\frac{\partial Y_k}{\partial X_i} = \sum_j \frac{\partial Y_k}{\partial B_j}\frac{\partial B_j}{\partial X_i} = \frac{1}{T^2} Y_k(1 - Y_k) \sum V_{jk} B_j (1 - B_j) W_{ij} \quad (4)$$

At the stage of sensitivity analysis, the threshold value and weights of the neural network have already been tuned by learning. In this study, the system was used to obtain the influence that the "X_i" value has on the "Y_k" value by calculating the output "Y_k" value when only the input item "X_i" was changed.

System No.1 in which there are three cells in an output layer and which has the highest correct answer rate for verification data was used for sensitivity analysis. The input data, excepting input items to be examined for sensitivity analysis, were prescribed as the mean value of all well data for which underground temperature was more than 200°C. The results of sample sensitivity analysis are shown in Figure 3 and Figure 4.

In both graphs, the certainty value is in the ordinate and the variable (an area of alteration halo for instance) is in the abscissa. The three curves are consequently shown for three ranges of different temperature in each graph. In such a graph, the obtained pair of curves which cross each other indicate that the response for



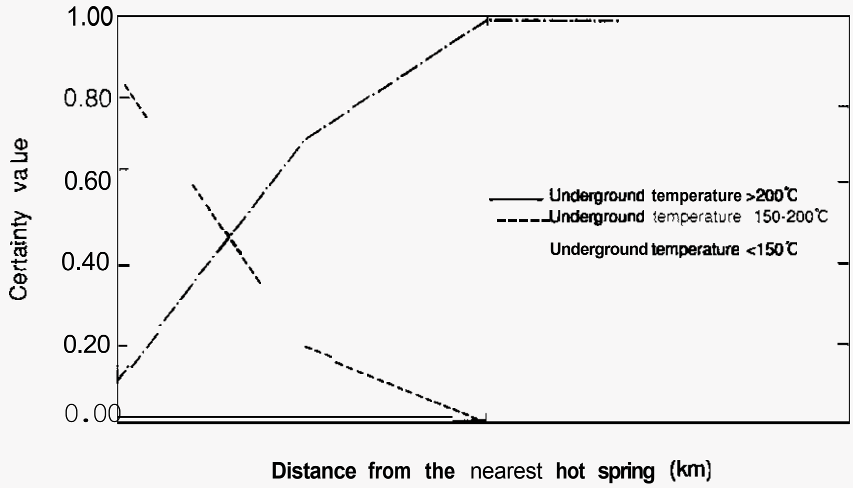


Figure 4 Relation between distance from the nearest hot spring and underground temperature

the output from input is large. When the pair of curves do not cross each other otherwise, the response is small.

Figure 3 shows the relation between the area of alteration halo and the certainty at three ranges of undergmund temperature. When the scale oi the area of alteration halo is small. the certainty of underground temperature < 150℃ is high. When it is large, the certainty of underground temperature of 150 - 200℃ is high. The underground temperature is quite sensitive to the area of alteration halo to distinguish hetween below 150℃ and 150 - 200℃. However. the sensitivity to distinguish between 150 – 200℃ and > 200℃ is not good. This means that the area of alteration halo applied in this study is quite useful to estimate whether the temperature is < 150℃ or 150 - 200℃ for the expected temperature of about 1000 - 1500 meters depth. This result in which the larger alteration halo is the more promising for high temperature shows the verification of usefulness oi the survey of alteration halo, though it is not much useful to distinguish hetween 150 - 200℃ and > 200℃.

Figure 4 shows the relation hetween the distance from the nearest hot spring and the certainty at three ranges of underground temperature. When the distance is small. the certainty of 150 – 200℃ is high. When it is large, the certainty of < 150℃ is high. This analysis shows the same kind of result to the alteration halo. In this case, the sensitivity to distinguish between 150 – 200℃ and < 150℃ is also good.

Consequently, in both cases the results are generally consistent with the empirical rules of geothermal prospecting.

6. CONCLUSION

The data of various kinds of surface survey and underground temperature measurement in the 149 drilled wells of which depths 1000 – 1500 meters were investigated by using neural network system. Three neural network systems were completed hy learning the data at the selected 20 areas of 24 areas. Thc systems were applied to estimate the underground temperature at depth of about 1000 – 1500 meters by using the data of surface surveys obtained at each area, and the estimated temperature at each area was verified to the measured one.

The verification results of the system in which learning was completed indicated that the correct-answer rate was about 50 – 70% and that the neural network system could be used successfully for estimating underground temperature. Howercr, comparing the judgements of the correct-answer for different temperature ranges, the numher of correct judgements for higher-temperature wells was less in all three systems investigated in this study. More obtained data of high temperature wells are required for learning data to improve the rate.

Based on the consideration in which the empirical usefulness of ground surface survey method could hc judged hy using the sensitivity analysis method. two kinds of method were investigated. The empirical rules hctween an area of alteration halo and the underground temperature, and a distance from the nearest hot spring and the undergmund temperature, were investigated respectively by using the method of sensitivity analysis.

In hoth cases, the results were consistent with the empirical rule except at the temperature range > 200℃. Besides these. the following results were obtained for the neural network system.

(1) The performance of the neural network depends on whether input data are in the form of direct value or rank value. Though the recognition rate of learning for the system composed hy using rank value instead ai direct one. was better than the rate by using direct value, the correct answer rate was worse on the contrary.

(2) In the systems ai No.1 and No.3, a different system is respectively composed hy changing the learning data. But comparing the correct answer rates of these two systems composed hy using different learning data for each other, there was not much difference hetween them.

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