Development of the ANN for the Estimation of Earth Parameter and Equivalent Resistivity

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Abstract - Earth equipments are essential to protect humans and other types of equipment from abnormal conditions. Earth resistance and potential must be restricted within a low value. An estimation algorithm of earth parameters and equivalent resistivity is introduced to calculate reliable earth resistance in this research. The proposed algorithm is based on the relationship between apparent resistances and earth parameters. The proposed algorithm, which approximates the non-linear characteristics of earth by using the Artificial Neural Network (ANN), estimates the earth parameters and equivalent resistivity. The effectiveness of the proposed method is verified with case studies.

Keywords: ANN, Earth parameter, Equivalent resistivity, MLP, SOM

1. Introduction

Earth equipments are essential to prevent the occurrence of an accident to humans or other types of equipment from abnormal conditions. When an unbalanced fault occurs, some fault currents flow down to earth through earth equipment. Therefore, electric potential around electrodes may arise. Hence, earth resistance and potential must be restricted within low value. The earth resistance varies according to the size and material of the electrode and the soil conditions. In particular, earth resistivity has great influence on earth resistance [1, 2]. The reliable estimation of structures and resistivity of the earth is essential when creating a viable plan. However, exact measurement is difficult because earth resistivity can be influenced by uncertain factors such as temperature, humidity, and etc.

In traditional methods, the earth structure is assumed to be in horizontal layer with several earth parameters, and then earth parameters and equivalent resistivity are estimated using apparent resistances. Structures are determined by an expert and earth parameters are estimated by the optimization method using apparent resistances measured by Wenner's method [3, 4]. Traditional estimation methods can be divided into the graphic method and the numerical method. The graphic method involves estimation by an expert. Its result is varied by the ability of expert or repeat calculation. Thus, it is hard to estimate the parameters precisely. The numerical method requires special techniques such as optimizing theory, and numerous calculations, whose results can be varied with initial values. Computer programs, which are a type of numerical method, are also sensitive to initial values [5, 6].

On considerations for non-linear characteristics of earth, artificial neural networks are induced to classify the structures and to estimate earth resistivities. The proposed algorithm can classify complex structures and estimate earth parameters that vary according to the ability of expert, complex numerous calculation, initial value problem, and so on [7, 8]. Recent researches have shown the possibility of Artificial Neural Networks(ANNs) [9-12].

In this paper, the estimation algorithm of the earth parameter and the equivalent resistivity using ANNs is presented. Self-Organizing Map(SOM) neural network is used to classify structures of soil and then the Multi-Layered Perceptron(MLP) neural networks are used to estimate earth parameters and resistivity.

In this research, using ANNs to earth modeling provides precise estimation of earth parameters and equivalent resistivity without a complex process. When input data are available, the reliable estimation of earth parameters and equivalent resistivity can be achieved. The effectiveness of the proposed method is verified with case studies.

2. Proposed Methods for Earth Parameters and Equivalent Resistivity Estimation

2.1 Overview

In traditional methods, earth parameters and equivalent resistivity are estimated using apparent resistances. Struc-

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tures are determined according to an expert, and then earth parameters are estimated by the optimization method.

In this research, earth structures are classified by SOM, which has excellent performance for pattern classification. There is a non-linear relationship between apparent resistance and earth parameters, and therefore earth parameters are estimated by MLP, which is famous as a non-linear function approximator.

Fig. 1 shows the procedure of this research. Actual $\rho - a$ data are acquired by field testing with Wenner's method. Earth parameters and equivalent resistivities are calculated by numerical method using computer-aided programs. Acquired data are divided into two groups for training and verification.

The ANNs are trained using a training data set. At first, structures of earth are classified using a SOM, and then MLP networks for earth parameters and equivalent resistivity estimation are trained respectively based on the result of structure classification. Verification data are used to test the accuracy of the ANNs.

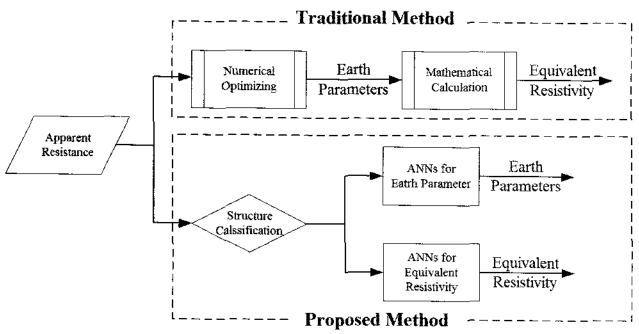

Fig. 1 Overview of proposed method

2.2 Structure Classification

Training data of SOM, apparent resistances acquired by field testing using Wenner's method, are classified into several data sets according to structures of earth by SOM.

Fig. 2 shows the concept of $\rho - a$ curve in the 2nd layered earth. ρ_a denotes apparent resistivity measured using Wenner's method. The spell, a and d indicate electrode separation and depth of first layer, respectively. When a is smaller than d, apparent resistivity incline to resistivity of first layer ρ_1, and ρ_a tends to ρ_2 in the opposite case. The 2nd layer structure can be classified by values of ρ_1 and ρ_2.

The right side of Fig. 2 illustrates variation of apparent resistances for ρ_1 and ρ_2 values.

To estimate earth parameters of a particular location, apparent resistances are needed. A set of apparent resistance constructs an input pattern of ANNs. Trained SOM classify earth structures by input pattern, and then MLP network, which combine with the input data to determine earth parameters.

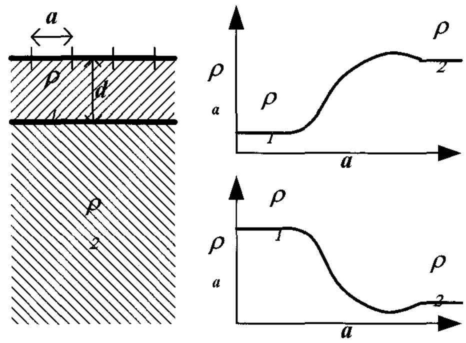

Fig. 2 Concept of the 2nd layer structure of earth

The SOM can be thought of as a nonlinear projection of the input pattern on the neuron array that represents the features of input patterns. The projection makes the topological neighborhood relationship geometrically explicit in low dimensional feature space.

The SOM consists of an input layer of neurons in a line and output layer constructed by neurons in a two-dimensional grid as shown in Fig. 3.

The SOM first determines the winning neuron in the competitive layer. Next, the weight vectors for all neurons within a certain neighborhood of the winning neuron are updated using the Kohonen rule.

SOM is implemented for the topological mapping from the multi-dimensional pattern of apparent resistances onto a two-dimensional plane. When the learning process is finished, mapping on identical neurons means that input patterns are equivalent and mapping on neighbor neurons means that input patterns are comparable to each other.

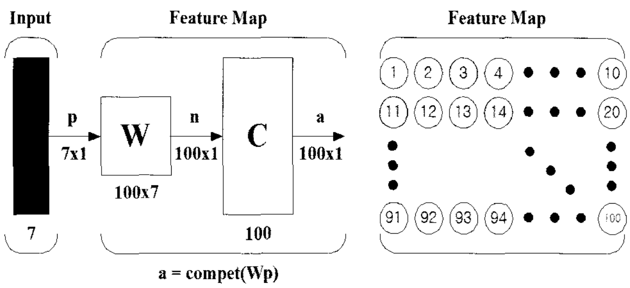

Fig. 3 Self-Organizing Feature Map

2.3 Earth parameters and resistivity estimation

Earth parameters and resistivity can be estimated using MLP. The training concept of ANNs for earth parameter estimation is illustrated in Fig. 4 as a block diagram. Apparent resistances were used for the input of each ANN, and earth parameters calculated by CDEGS were used for target values. Outputs of MLP are compared with target value, and then sum-squired error is used to adjust the weight. During the learning process of the ANN, the weights are updated to minimize error. Training of MLP is based on the error back-propagation algorithm.

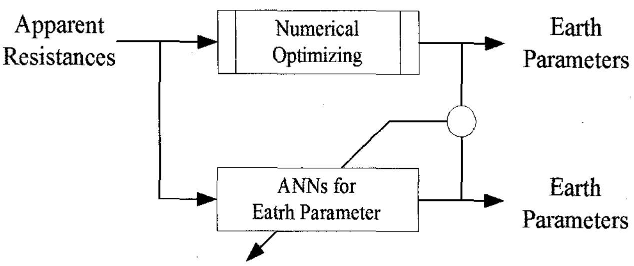

Fig. 4 Earth parameter estimation with ANNs

Generally, structure of the MLP is constructed of more than three layers; input, output, and hidden layer. But, the precise method for structure determination has not yet been presented. Therefore, it is constructed by trial and error.

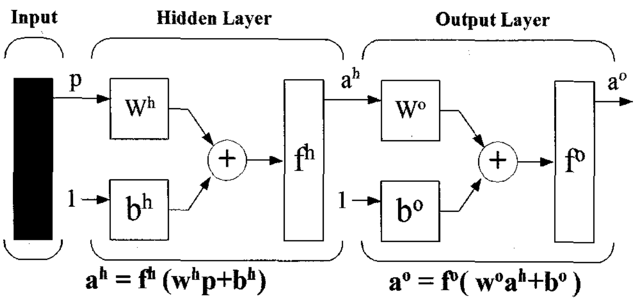

Fig. 5 Multi-layer perceptron

Fig. 5 presents the concept of MLP. At the input layer, each neuron's output is simply equal to its input. In the hidden and output layers, each neuron determines its output by weighted sum and activation function. Each input vector is passed forward through the network, and an output vector is calculated by (1).

$$\begin{aligned} \mathbf{a}^o &= f^o\left(\mathbf{W}^o\mathbf{a}^h + \mathbf{b}^o\right) \\ \mathbf{a}^h &= f^h\left(\mathbf{W}^h\mathbf{p} + \mathbf{b}^h\right) \end{aligned} \tag{1}$$

Where, $\mathbf{a}^o$: output of MLP (earth parameters),
$\mathbf{a}^h$: output of hidden layer,
$\mathbf{p}$: input vector (rho-a data),
f: activation function,
$\mathbf{W}$: weight matrix,
$\mathbf{b}$: bias.

The numbers of MLPs for earth parameter estimation are determined by structures classified by SOM, as are the MLPs for earth resistivity estimation. After training, accuracy of the MLPs is verified using a verification data set.

3. Case Study

3.1 Field test data

Input data used in this research are acquired by field testing. Apparent resistances are measured by SAS-300C based on Wenner's method [14].

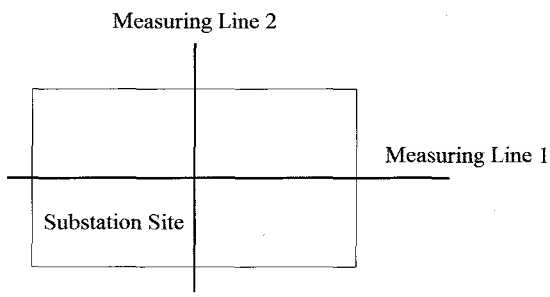

Fig. 6 Example of measuring plan for earth resistivity

As indicated in Fig. 6, field testing is performed through measuring lines at a substation site. Measuring lines are selected as orthogonal to each other as possible to obtain uniform apparent resistances. Earth parameters, which used to target data of the ANNs, are calculated using CDEGS.

500 data sets were achieved and 400 of these were used for training. 100 data sets were remained to assist in the verification process. Tables 1 and 2 show the verification data, which were selected based on apparent resistance measured by electrode separations. Table 1 shows the DU case in which apparent resistance values were increased by electrode separations and Table 2 shows the UD case.

Table 1 Apparent resistivities by electrode separations [DU case]

Num.	Input data (rho [m])						
	2 [m]	4 [m]	6 [m]	10 [m]	15 [m]	20 [m]	30 [m]
1	192.12	213.40	296.08	370.88	392.92	395.28	400.00
2	165.08	253.96	228.56	349.20	333.32	355.72	400.00
3	242.28	301.72	359.32	400.00	377.16	361.16	329.16
4	279.12	320.00	330.68	355.56	400.00	379.56	338.68
5	160.00	240.00	320.00	360.00	392.00	396.00	400.00
6	336.21	373.45	518.14	649.04	687.61	691.74	700.00
7	288.89	444.43	399.98	611.10	583.31	622.51	700.00
8	423.99	528.01	628.81	700.00	660.03	632.03	576.03
9	488.46	560.00	578.69	622.23	700.00	664.23	592.69
10	280.00	420.00	560.00	630.00	686.00	693.00	700.00
11	624.39	693.55	962.26	1,205.4	1,277.0	1,284.7	1,300.0
12	536.51	825.37	742.82	1,134.9	1,083.3	1,156.1	1,300.0
13	787.41	980.59	1,167.8	1,300.0	1,225.8	1,173.8	1,069.8
14	907.14	1,040.0	1,074.7	1,155.6	1,300.0	1,233.6	1,100.7
15	520.00	780.00	1,040.0	1,170.0	1,274.0	1,287.0	1,300.0
16	1,200.8	1,333.8	1,850.5	2,318.0	2,455.8	2,470.5	2,500.0
17	1,031.8	1,587.3	1,428.5	2,182.5	2,083.3	2,223.3	2,500.0
18	1,514.3	1,885.8	2,245.8	2,500.0	2,357.3	2,257.3	2,057.3
19	1,744.5	2,000.0	2,066.8	2,222.3	2,500.0	2,372.3	2,116.8
20	1,000.0	1,500.0	2,000.0	2,250.0	2,450.0	2,475.0	2,500.0

3.2 Structure classification of earth

Generally, initial weights of SOM are set random values at initial learning, but initial weights are set medial values of input patterns to increase learning efficiency in this research. Numbers of iterations are 7,920 (330 input patterns, neighborhood, 3 repeat). Numbers of neighborhood neurons were determined by maximum Manhattan distance. Weights were updated using a winner-take-all algorithm [15].

Table 2 Apparent resistivities by electrode separations [UD case]

Num.	Input data (rho [m])						
	2 [m]	4 [m]	6 [m]	10 [m]	15 [m]	20 [m]	30 [m]
1	400.00	256.04	151.12	112.44	127.84	116.76	141.44
2	400.00	237.88	117.80	108.40	103.04	105.52	126.44
3	400.00	330.00	213.28	142.76	130.88	136.00	161.96
4	240.00	400.00	360.00	160.00	144.00	148.00	156.00
5	400.00	342.84	252.84	295.24	300.00	290.48	271.44
6	700.00	448.07	264.46	196.77	223.72	204.33	247.52
7	700.00	416.29	206.15	189.70	180.32	184.66	221.27
8	700.00	577.50	373.24	249.83	229.04	238.00	283.43
9	420.00	700.00	630.00	280.00	252.00	259.00	273.00
10	700.00	599.97	442.47	516.67	525.00	508.34	475.02
11	1,300.0	832.13	491.14	365.43	415.48	379.47	459.68
12	1,300.0	773.11	382.85	352.30	334.88	342.94	410.93
13	1,300.0	1,072.50	693.16	463.97	425.36	442.00	526.37
14	780.00	1,300.00	1,170.00	520.00	468.00	481.00	507.00
15	1,300.0	1114.2	821.73	959.53	975.00	944.06	882.18
16	2,500.0	1,600.30	944.50	702.75	799.00	729.75	884.00
17	2,500.0	1,486.8	736.25	677.50	644.00	659.50	790.25
18	2,500.0	2,062.50	1,333.00	892.25	818.00	850.00	1,012.30
19	1,500.0	2,500.00	2,250.00	1,000.00	900.00	925.00	975.00
20	2,500.0	2,142.80	1,580.30	1,845.30	1,875.00	1,815.50	1,696.50

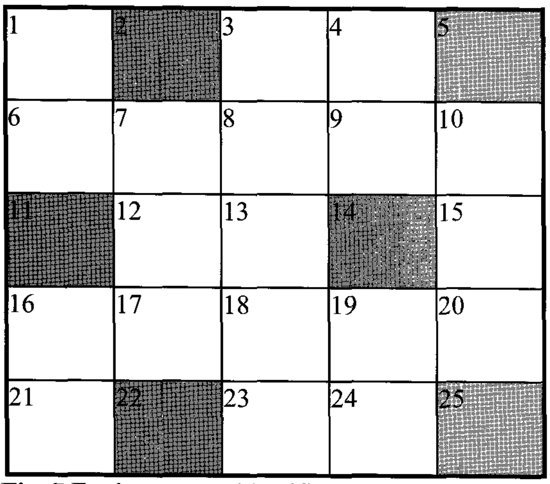

Fig. 7 Earth structure identification results by SOM

If neurons of the output layer are set too small, then input patterns are classified roughly. Thus, neurons of the output layer were searched from 3×3 to 10×10 for reasonable structure. Initial learning rate was set at 0.02 and decreased during the learning process. 330 input patterns are used in the SOM training.

Classification results are overlapped when SOM has 3×3 and 4×4 neurons of output layer and scattered when SOM has over 6×6 neurons of output layer. Therefore, 5×5 neurons are selected in this research, and results are indicated in Fig. 7. Fig. 8 shows examples of classified patterns.

3.3 Estimation of earth parameters

MLPs for earth parameter estimation are constructed based on the result of SOM classification. Because performance of the MLP can be varied by number of hidden neurons, results of variation are analyzed from 10 to 30 neurons in this research. Neurons of hidden layer are determined to be 25 by analyses. Input and output neurons of MLP were 7 and 3 neurons, respectively. Initial learning rate and momentum were 0.1 and 0.85, respectively. Maximum iteration is 10,000 at the learning stage.

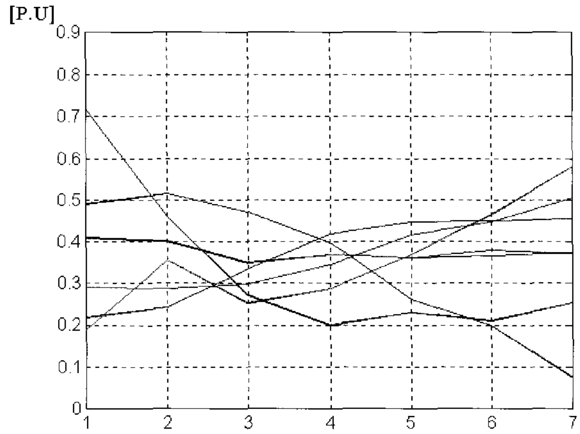

Fig. 8 Examples of classified ρ_a curves

At the verification stage, outputs of MLP are compared with results of CDEGS. Tables 3 and 4 show the comparison results. Errors of Tables 3 and 4 are calculated by average of absolute error as indicated in (2).

$$E_a = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{t_i - c_i}{t_i}\right| \times 100 \tag{2}$$

Where, t_i : Target value, c_i : Output of MLP, n : Number of data

As shown in Tables 3 and 4, average estimation errors of earth parameters result in 0.79, 0.14, and 1.35[%] in the DU case and 0.13, 0.08, and 0.99[%] in the UD case. Results of MLP were almost reasonable, but maximum error of h was 13[%]. This result is regarded as an electrode separations problem.

Table 3 Estimation results of earth parameter by ANN [DU case]

Num	Target Values			Computed Values			Error [%]		
	ρ_1[Ω]	ρ_2	h	ρ_1[Ω]	ρ_2[Ω]	h	ρ_1	ρ_2	h[m]
1	168.36	449.77	2.60	168.04	450.40	2.59	0.19	0.14	0.48
2	150.49	408.58	2.45	150.00	408.08	2.45	0.32	0.12	0.16
3	201.10	374.74	1.30	201.04	374.44	1.31	0.03	0.07	0.79
4	256.98	375.23	1.79	258.52	375.47	1.84	0.59	0.06	2.66
5	107.60	439.03	1.33	106.85	438.75	1.32	0.69	0.06	0.61
6	294.17	786.65	2.59	294.07	788.20	2.59	0.03	0.19	0.09
7	263.72	715.43	2.46	262.50	714.15	2.45	0.46	0.17	0.24
8	351.79	655.55	1.30	351.82	655.27	1.31	0.00	0.04	0.79
9	453.55	657.10	1.85	452.40	657.08	1.84	0.25	0.00	0.66
10	188.52	767.83	1.33	186.98	767.82	1.32	0.8	0.00	0.61
11	546.82	1461.6	2.60	546.12	1463.80	2.59	0.12	0.14	0.48
12	488.97	1327.9	2.45	487.50	1326.30	2.45	0.30	0.12	0.16
13	653.57	1217.9	1.30	653.37	1216.90	1.31	0.03	0.07	0.79
14	838.42	1219.2	1.82	840.18	1220.30	1.84	0.20	0.08	0.97
15	385.30	1437.2	1.52	347.26	1425.90	1.32	9.87	0.78	13.03
16	1052.20	2810.9	2.60	1050.20	2815.00	2.59	0.18	0.14	0.48
17	939.09	2552.9	2.44	937.50	2550.50	2.45	0.16	0.09	0.57
18	1257.90	2344.1	1.31	1256.50	2340.30	1.31	0.11	0.16	0.02
19	1628.80	2346.8	1.89	1615.70	2346.70	1.84	0.80	0.00	2.76
20	672.88	2733.9	1.33	667.80	2742.20	1.32	0.75	0.30	0.61

Table 4 Estimation results of earth parameter by ANN [UD case]

Num	Target Values			Computed Values			Error [%]		
	ρ_1	ρ_2	h[m]	ρ_1	ρ_2	h[m]	ρ_1	ρ_2	h[m]
1	451.1	115.0	2.17	452.7	115.0	2.11	0.34	0.00	2.55
2	493.3	102.3	1.87	492.4	102.3	1.90	0.17	0.02	1.66
3	486.3	128.6	2.58	485.5	128.9	2.60	0.15	0.21	0.68
4	294.9	134.6	4.72	294.9	134.7	4.72	0.01	0.04	0.08
5	312.6	258.2	10.44	312.6	257.8	10.44	0.00	0.14	0.00
6	789.5	201.2	2.17	792.2	201.2	2.11	0.34	0.00	2.55
7	863.4	179.0	1.87	861.8	179.0	1.90	0.17	0.01	1.66
8	851.0	225.1	2.58	849.7	225.6	2.60	0.15	0.21	0.68
9	516.1	235.6	4.72	516.1	235.7	4.72	0.01	0.04	0.08
10	547.1	451.8	10.44	547.1	451.2	10.44	0.00	0.13	0.00
11	1466.	373.7	2.17	1471.	373.8	2.11	0.34	0.00	2.55
12	1603.	332.5	1.87	1600.	332.5	1.90	0.17	0.02	1.66
13	1580.	418.1	2.58	1578.	419.0	2.60	0.15	0.21	0.68
14	958.5	437.5	4.72	958.6	437.7	4.72	0.01	0.04	0.08
15	1016.	839.1	10.44	1016.	838.0	10.44	0.00	0.13	0.00
16	2819.	718.8	2.17	2829.	718.8	2.11	0.34	0.00	2.55
17	3083.	639.4	1.87	3078.	639.5	1.90	0.17	0.02	1.66
18	3039.	804.0	2.58	3034.	805.8	2.60	0.16	0.22	0.68
19	1843.	841.4	4.72	1843.	841.8	4.72	0.01	0.04	0.08
20	1954.	1613.	10.44	1954.	1611.	10.44	0.00	0.14	0.00

3.4 Equivalent resistivity estimation

In training MLPs for equivalent resistivity estimation, the number of hidden neurons also has influence over the performance of MLP. 10 to 25 hidden neurons were analyzed in this research to find an adaptable network. Initial conditions were 0.1 learning rate, 0.85 momentum, and 10,000 maximum iterations. Analysis results are shown in Table 5 at each case. Errors of MLPs were calculated using sum-squired error as shown in (3).

$$E_s = \frac{1}{n}\sqrt{\sum_{i=1}^{n}(t_i - c_i)^2} \times 100 \tag{3}$$

Where, t_i : Target value, c_i : Output of MLP, n : Number of data

Table 5 Estimation result errors of earth resistivity as hidden neurons

Number of hidden neurons	Sum-squired error[%]
10	0.0565
15	0.1810
18	0.0033
20	0.0040
25	0.0080

Table 5 presents variations of estimation error to change of hidden neurons. The number of hidden neurons was selected to be 18 neurons based on this result.

Verification results of equivalent resistivity estimation were summarized in Table 6. Maximum and average errors are 0.196[%] and 0.120[%] in the DU case, and 1.533[%] and 0.591[%] in the UD case. Figs. 9 and 10 illustrate results of the equivalent resistivity estimation.

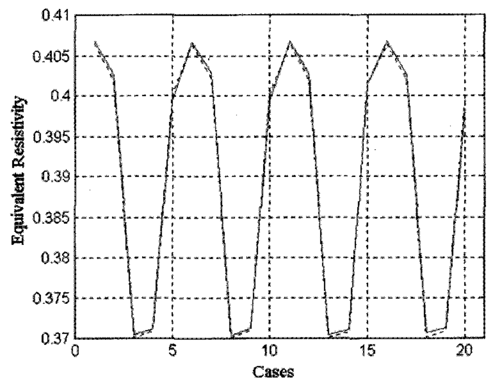

Fig. 9 Estimation results of earth resistivity by ANN [DU case]

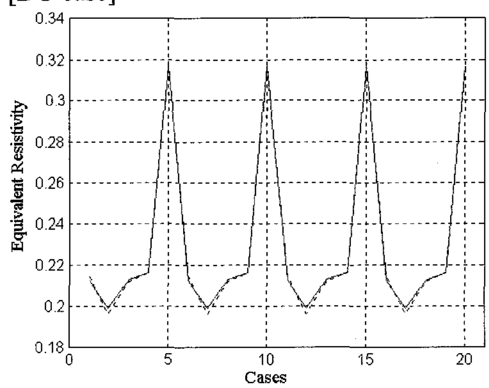

Fig. 10 Estimation results of earth resistivity by ANN [UD case]

Table 6 Estimation results of earth resistivities by ANN

	DU Case			UD Case		
	Target value	Computed value	Error [%]	Target value	Computed value	Error [%]
1	392.84	392.57	0.0687	121.54	122.60	0.8750
2	358.44	357.86	0.1618	107.64	105.99	1.5320
3	361.18	360.79	0.1080	137.35	136.85	0.3673
4	365.23	364.96	0.0739	147.24	147.07	0.1157
5	386.18	386.94	0.1968	274.87	274.68	0.0689
6	687.31	686.96	0.0509	212.70	214.56	0.8728
7	627.48	626.28	0.1912	188.37	185.48	1.5320
8	631.89	631.36	0.0839	240.37	239.48	0.3703
9	639.42	638.89	0.0829	257.67	257.37	0.1157
10	675.52	676.92	0.2072	481.02	480.69	0.0684
11	1276.70	1275.80	0.0705	395.02	398.46	0.8714
12	1164.90	1163.00	0.1631	349.83	344.47	1.5320
13	1173.80	1172.60	0.1022	446.40	444.75	0.3700
14	1186.60	1185.80	0.0674	478.53	477.98	0.1157
15	1262.70	1263.20	0.0396	893.32	892.71	0.0682
16	2455.20	2453.50	0.0692	759.65	766.27	0.8719
17	2239.60	2235.90	0.1652	672.76	662.44	1.5334
18	2259.00	2255.20	0.1682	858.39	855.28	0.3621
19	2283.30	2281.70	0.0701	920.24	919.18	0.1147
20	2407.30	2413.70	0.2659	1717.92	1716.75	0.0680
Average error	-	-	**0.1203**	-	-	**0.5913**

4. Conclusion

An estimation algorithm of earth parameters and equivalent resistivity is introduced in this research. The proposed algorithm is based on the relationship between apparent resistivities and earth parameters. This method is easier than traditional complex processes by using ANN, which approximates the non-linear characteristics of earth. Results of this research can be summarized as follows. The structure classification method using SOM was introduced, and the results of classification were shown. Earth parameter estimation was performed using MLPs. The estimation errors of earth parameters result in 0.79, 0.14, and 1.35[%] in the DU case and 0.13, 0.08, and 0.99[%] error in the UD case. MLPs for equivalent resistivity estimation were constructed by 7-input neurons, 18-hidden neurons, and 1 output neuron. Estimation errors were 0.120[%] and 0.591[%] in each case.

The proposed method integrates the advantages of the graphic method and numerical method with artificial neural networks. It has some advantages in that less time is required with improved precision and more reliability. Constraints of this research are constructed from the layers of earth, the electrode separation and the equivalent earth depth. For more adaptivity and reliability, a more reliable field test method and various separation data are needed.

Acknowledgements

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References

[1] G. F. Tagg, *Earth Resistances*, 1964.

[2] O. H. Gish, W. J. Rooney, "Measurement of Resistivity of Large Masses of Undisturbed Earth," *Terrestrial Magnetism and Atmospheric Electricity*, Vol. 30, pp. 161.

[3] E. Lancaster-Jones, "The Earth-Resistivity Method of Electrical Prospecting," *The Mining Magazine*, June 1930.

[4] F. Dawalibi, C. J. Blattner, "Earth Resistivity Measurement Interpretation Technique," *IEEE PAS*, Vol. 103. No. 2, pp. 374-382, Feb. 1984.

[5] J. L. del Alamo, "A Comparison Among Eight Different Techniques to Achieve an Optimum Estimation of Electrical Grounding Parameters in Two-Layered Earth," *IEEE Trans. on Power Delivery*, Vol. 8, No. 4, pp. 1890-1899, Oct. 1993.

[6] T. Takahashi, T. Kawase, "Analysis of Apparent Resistivity in a Multi-Layer Earth Structure," *IEEE Trans. on Power Delivery*, Vol. 5, No. 2, pp. 604~612, 1990.

[7] Hans R. Seedher, J.K. Arora, "Estimation of Two Layer Soil Parameters Using Finite Wenner Resistivity Expressions," *IEEE Trans. on Power Delivery*, Vol. 7, No. 3, pp. 1,213~1,217, 1992.

[8] SES (Safe Engineering Services & Technologies Ltd.), CDEGS (Current Distribution, Electromagnetic Fields, Grounding and Soil Structure Analysis) Manual, Version 2.5.3, 1995.

[9] P.S.Ji et al., "Earth Resistivity Estimation Using Artificial Neural Network," *ICEE '98*, Vol. 2, pp. 469-472, July, 1998.

[10] Ryu Bo-hyuk, Wee Won-Seok, Kim Jung-Hoon, "A Study on Methodology of Soil Resistivity Estimation Using the BP," *Trans. KIEE*, Vol. 51A, No. 2, pp. 76-82, Feb., 2002.

[11] J.P. Lee, P.S. Ji, and J.Y. Lim, "Estimation of Earth Parameters Using Neural Network," *KIEE and IEEK Joint Fall Con. 2003 for Chungbuk Branch*, Vol. 2, pp. 71-74, Nov, 2003.

[12] J.P. Lee, P.S. Ji, and J.Y. Lim, "Earth Structure Modeling Using Neural Network," *KIEE Summer Annual Conference 2004*, pp. 569-571, July, 2004.

[13] Jer-Nan Juang, *Applied System Identification*, Prentice Hall, Inc.pp. 3-14, 1994.

[14] ABEM Terrameter SAS-300C Catalogue.

[15] Martin T. Hagan, Howard B. Demuch, and Mark Beale, *Neural Network Design*, Thomson Learning, pp. 14-1~15, 1996.

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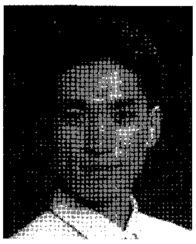

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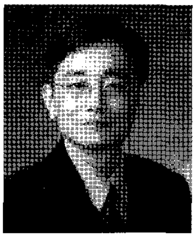

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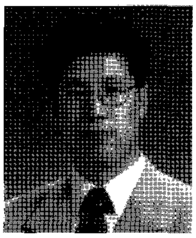

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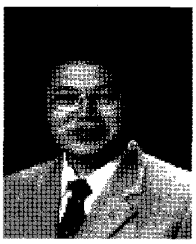

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