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A Sensitivity Analysis of Design Parameters of an Underground Radioactive Waste Repository Using a Backpropagation Neural Network

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Backpropagation 인공신경망을 이용한 지하 방사성폐기물 처분장 설계 인자의 민감도 분석

권상기, 조원진

Abstract The prediction of near field behavior around an underground high-level radioactive waste repository is important for the repository design as well as the safety assessment. In this study, a sensitivity analysis for seven parameters consisted of design parameters and material properties was carried out using a three-dimensional finite difference code. From the sensitivity analysis, it was found that the effects of borehole spacing, tunnel spacing, cooling time and rock thermal conductivity were more significant than the other parameters. For getting a statistical distribution of buffer and rock temperatures around the repository, an artificial neural network, backpropagation, was applied. The reliability of the trained neural network was tested with the cases with randomly chosen input parameters. When the parameter variation is within ±10%, the prediction from the network was found to be reliable with about a 1% error. It was possible to calculate the temperature distribution for many cases quickly with the trained neural network. The buffer and rock temperatures showed a normal distribution with means of 98°C and 83.9°C standard deviations of 3.82°C and 3.67°C, respectively. Using the neural network, it was also possible to estimate the required change in design parameters for reducing the buffer and rock temperatures for 1°C.

Key words HLW repository, backprogagation, sensitivity analysis, FLAC3D, buffer

초 록 지하고준위 방사성폐기물 처분장 근계영역에서의 거동을 예측하는 것은 처분장 설계나 안전성 평가에 중요하다. 본 연구에서는 3차원 유한차분 코드를 이용하여 처분장 설계인자 및 재료물성으로 구성되는 7가지 인자에 대한 민감도 분석을 실시하였다. 민감도 분석 결과 처분공 간격, 터널 간격, 냉각시간과 암반의 열전도도가 다른 인자에 비해 영향이 큰 것으로 나타났다. 처분장 주변의 암반과 완충재 온도의 통계적인 분포를 구하기 위해 backpropagation 인공신경망 기법이 적용되었다. 학습된 인공신경망의 적합성을 평가하기 위해 무작위로 선정된 입력 인자에 대한 예측이 실시되었다. 인자 값의 변화가 ±10% 인 경우, 신경망은 1% 오차로 신뢰할 수 있는 예측 결과를 보임을 알 수 있었다. 이렇게 학습된 신경망은 다양한 경우에 대한 신속한 온도 예측에 활용할 수 있었다. 완충재와 암반의 온도는 각각 평균 98°C, 83.9°C 표준편차는 3.82°C 와 3.67°C로 나타났다. 인공신경망을 이용함으로써 암반과 완충재 온도를 1°C 변화시키기 위해 필요한 설계 인자의 조정 범위를 추정할 수 있었다.

핵심어 고준위처분장, Backpropagation, 민감도 분석, FLAC3D, 완충재

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1. Introduction

The suggestion of a reliable solution for a safe management of high-level radioactive wastes (HLW) including spent fuels is an urgent issue in many countries utilizing nuclear energy. To dispose of the radioactive waste in a geological formation, it is required to understand the overall behavior of the design parameters in the deep underground repository conditions. One of the unique characteristic of HLW is the heat generation from the waste. Even after tens of years of cooling in the pools at reactor sites, significant heat is generating for a long time after the emplacement of the waste in an underground repository. The understanding of the influence of the decay heat on mechanical, hydraulic, and chemical behaviors of the disposal system is an important issue for the design of the repository as well as the safety assessment of the system.

Normally the distribution of heat in a geological repository system is predicted using computer simulations. Because of the influence of discontinuities and other geo-environmental parameters, rock properties around an underground excavation cannot be consistent but vary. Such a rock property variation should be considered in the calculation of the temperature distribution. At that point of view, a statistical approach is highly recommended for a reliable prediction of the behavior of rock mass under a repository condition. The only problem to achieve a statistical distribution of the temperatures around a disposal tunnel is the long calculation time required to run a three-dimensional model with a complex geometry.

It would be possible to use some empirical equations for calculating the temperature distribution around an underground repository. However, empirical equations can be applied only to general cases not to complex cases with different material properties, rock property change in EDZ, and three-dimensional condition.

In this study, therefore, a sensitivity analysis for different material properties, which can influence on the temperature distribution in the near field close to the waste, was carried out with a three-dimensional finite difference code. The temperatures at important locations were used for training an artificial neural network and then the trained network was tested using the temperatures from different cases with randomly chosen design parameters. When it was confirmed that the trained network works well for the temperature prediction, it was applied for estimating the statistical distribution of temperatures.

2. HLW disposal concept and decay heat

In Korea, 20 nuclear power plants are operating and producing significant amount of spent fuels. Currently more than 9500 tons of spent fuels had been produced and temporarily stored at the reactor sites. With regard to the safe management of the spent fuels, a long-term R&D program was started in 1997 and a Korean reference disposal system, KRS, could be suggested in 2006 (Lee et al., 2006).

According to the KRS, the spent fuels will be encapsulated in corrosion resistant canisters and disposed of in a deep underground repository constructed in a crystalline rock located at 500 m below the surface. Compacted bentonite buffer will be installed surrounding the canisters for various purposes. In the KRS, the canisters containing Pressurized Water Reactor (PWR) and Canadian Deuterium Uranium Reactor (CANDU) spent fuels are assumed to be emplaced in the vertical boreholes drilled with spacing of 6 m and 4 m, respectively, in the floor (Lee et al., 2006). The borehole spacing and tunnel spacing were determined based on the thermal calculation to satisfy that the buffer temperature should be lower than 100°C. In order to dispose of the spent fuel expected to be generated during the life time of the Korean nuclear power

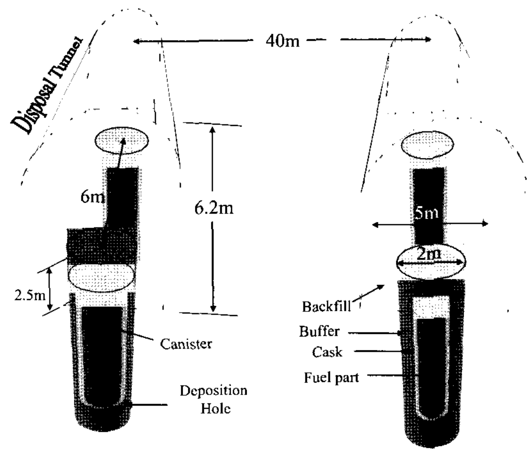

Fig. 1. Disposal tunnel and deposition hole concept for the Korean reference disposal system.

plants in an underground repository, more than 4 km^2 underground repository is required. Since the principal repository design is determined based on the thermal criteria, it is highly recommended to clearly understand the thermal behavior at the repository design as well as safety assessment point of views.

The mixture of bentonite and crushed rock is considered as the backfilling material. Backfilling is assumed to be done immediately after the emplacement of canister and buffer. Fig. 1 shows the conceptual design of the disposal tunnel and deposition hole. Further description of Korean reference disposal concept can be found KAERI reports (Lee, et al., 2005).

3. Sensitivity analysis of near field on temperature

3.1 Model mesh and initial condition

For the detailed thermal analysis, the disposal tunnel, fuel part, cask, backfill, buffer, excavation damaged zone (EDZ) and rock were included separately in the model as shown in Fig. 2. The surface temperature was assumed to be 15°C and a geothermal gradient of 3°C/100 m was used. For the PWR spent fuel generated from the Korean nuclear power plants, the decay heat can be calculated using the following equation (Choi et al., 1997);

$$P(t) = 14548 \times t^{-0.76204} \quad (W / year) \quad t > 30 \text{ years} \quad (1)$$

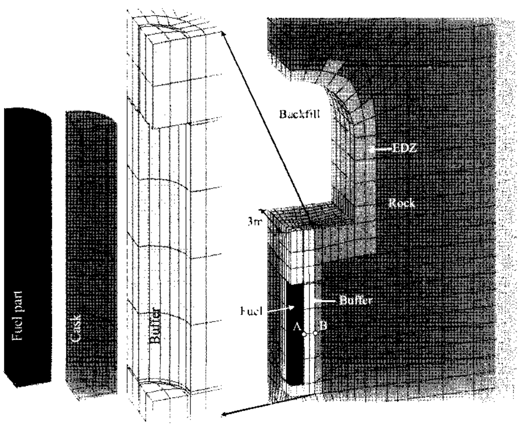

Fig. 2. Model mesh for the HLW repository at 500m deep underground.

where, t is the elapsed time (year) after extracting the spent fuel from a reactor.

3.2 Parameters for sensitivity analysis

A sensitivity analysis was carried out for investigating the influence of different design parameters and material properties on thermal behavior around an underground HLW disposal tunnel. Seven parameters including the thermal properties and major repository parameters such as tunnel and deposition hole spacing were varied ±10% from their reference properties, which were used for the KRS development. Cooling time represents that the elapsed time since the release of the spent fuel from nuclear reactor. For the sensitivity analysis of the seven parameters, a full factorial design was applied and the variation of the parameters for 64 cases are listed in Table 1.

3.3 Calculation results

For each case, the temperature variation with time was calculated for 200 years using FLAC3D (Itasca, 2002). Fig. 3 shows a typical temperature change of buffer and rock with time. The buffer and rock temperatures increase rapidly after the emplacement of PWR spent fuel in a deposition hole and then smoothly decrease with time. Since it is normal to arrive the peak temperature of buffer and rock before 100 years, the calculation time of 200 years is long enough to check the peak temperatures for the 64 cases. After calculation, the peak temperatures at buffer and rock were checked and used for the following sensitivity analysis.

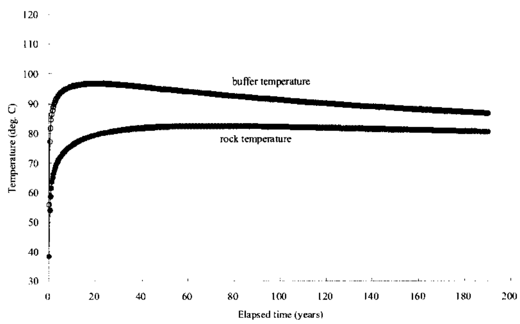

Fig. 3. The variation of buffer and rock temperatures with time for the case with reference input parameters.

Table 1. Input values for the 64 cases from a full factorial design

Case	*Hole Spacing (m)*	*Tunnel spacing (m)*	*Cooling time (year)*	*Rock T.C. (W/m°K)*	*Buffer T.C. (W/m°K)*	*Backfill T.C. (W/m°K)*	*EDZ T.C. (W/m°K)*
1	6.6	44	44	2.75	1.1	2.2	3.85
2	6.6	44	44	2.75	1.1	1.8	3.15
3	6.6	44	44	2.75	0.9	2.2	3.15
4	6.6	44	44	2.75	0.9	1.8	3.85
5	6.6	44	44	2.25	1.1	2.2	3.15
6	6.6	44	44	2.25	1.1	1.8	3.85
7	6.6	44	44	2.25	0.9	2.2	3.85
8	6.6	44	44	2.25	0.9	1.8	3.15
9	6.6	44	36	2.75	1.1	2.2	3.15
10	6.6	44	36	2.75	1.1	1.8	3.85
11	6.6	44	36	2.75	0.9	2.2	3.85
12	6.6	44	36	2.75	0.9	1.8	3.15
13	6.6	44	36	2.25	1.1	2.2	3.85
14	6.6	44	36	2.25	1.1	1.8	3.15
15	6.6	44	36	2.25	0.9	2.2	3.15
16	6.6	44	36	2.25	0.9	1.8	3.85
17	6.6	36	44	2.75	1.1	2.2	3.15
18	6.6	36	44	2.75	1.1	1.8	3.85
19	6.6	36	44	2.75	0.9	2.2	3.85
20	6.6	36	44	2.75	0.9	1.8	3.15
21	6.6	36	44	2.25	1.1	2.2	3.85
22	6.6	36	44	2.25	1.1	1.8	3.15
23	6.6	36	44	2.25	0.9	2.2	3.15
24	6.6	36	44	2.25	0.9	1.8	3.85
25	6.6	36	36	2.75	1.1	2.2	3.85
26	6.6	36	36	2.75	1.1	1.8	3.15
27	6.6	36	36	2.75	0.9	2.2	3.15
28	6.6	36	36	2.75	0.9	1.8	3.85
29	6.6	36	36	2.25	1.1	2.2	3.15
30	6.6	36	36	2.25	1.1	1.8	3.85
31	6.6	36	36	2.25	0.9	2.2	3.85
32	6.6	36	36	2.25	0.9	1.8	3.15
33	5.4	44	44	2.75	1.1	2.2	3.15
34	5.4	44	44	2.75	1.1	1.8	3.85
35	5.4	44	44	2.75	0.9	2.2	3.85
36	5.4	44	44	2.75	0.9	1.8	3.15
37	5.4	44	44	2.25	1.1	2.2	3.85
38	5.4	44	44	2.25	1.1	1.8	3.15
39	5.4	44	44	2.25	0.9	2.2	3.15
40	5.4	44	44	2.25	0.9	1.8	3.85

Table 1. Input values for the 64 cases from a full factorial design (continue)

38	5.4	44	44	2.25	1.1	1.8	3.15
39	5.4	44	44	2.25	0.9	2.2	3.15
40	5.4	44	44	2.25	0.9	1.8	3.85
41	5.4	44	36	2.75	1.1	2.2	3.85
42	5.4	44	36	2.75	1.1	1.8	3.15
43	5.4	44	36	2.75	0.9	2.2	3.15
44	5.4	44	36	2.75	0.9	1.8	3.85
45	5.4	44	36	2.25	1.1	2.2	3.15
46	5.4	44	36	2.25	1.1	1.8	3.85
47	5.4	44	36	2.25	0.9	2.2	3.85
48	5.4	44	36	2.25	0.9	1.8	3.15
49	5.4	36	44	2.75	1.1	2.2	3.85
50	5.4	36	44	2.75	1.1	1.8	3.15
51	5.4	36	44	2.75	0.9	2.2	3.15
52	5.4	36	44	2.75	0.9	1.8	3.85
53	5.4	36	44	2.25	1.1	2.2	3.15
54	5.4	36	44	2.25	1.1	1.8	3.85
55	5.4	36	44	2.25	0.9	2.2	3.85
56	5.4	36	44	2.25	0.9	1.8	3.15
57	5.4	36	36	2.75	1.1	2.2	3.15
58	5.4	36	36	2.75	1.1	1.8	3.85
59	5.4	36	36	2.75	0.9	2.2	3.85
60	5.4	36	36	2.75	0.9	1.8	3.15
61	5.4	36	36	2.25	1.1	2.2	3.85
62	5.4	36	36	2.25	1.1	1.8	3.15
63	5.4	36	36	2.25	0.9	2.2	3.15
64	5.4	36	36	2.25	0.9	1.8	3.85
Reference value	6	40	40	2.5	1.0	2	3.5

3.4 Major effect

Using the calculation results from the 64 cases, it is possible to determine the relative effect of the parameters on the peak temperatures at buffer and rock. The effect of each parameter can be determined as following:

$$E_k = \frac{\sum_{i=1}^{32} TEMP_{k,i} - \sum_{j=1}^{32} temp_{k,j}}{32} \quad (2)$$

Where, E_k is the main effect of kth parameter. $TEMP_k$ and $temp_k$ are the temperature for the cases with higher and lower value of kth parameter, respectively. The main effects of the parameters on the peak rock and buffer temperatures are shown in Fig. 4. Negative main effect of a parameter means that the temperature decreases with an increase of the parameter. In the case of the deposition hole spacing, which was found to be the most critical parameter, the buffer temperature decreased by almost 8°C when the hole spacing increased from 5.4 m to 6.6 m.

When the parameters vary in a given range from the reference values, the influence of deposition hole spacing on both of rock and buffer temperatures is the strongest. For the peak buffer temperature, cooling time

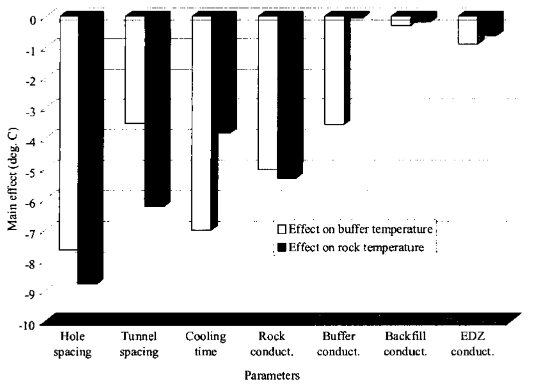

Fig. 4. Main effect of the seven parameters on buffer and rock temperatures.

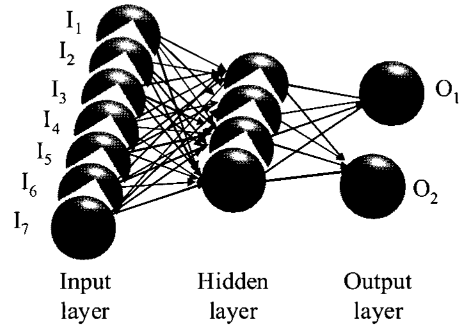

Fig. 5. The structure of the neural network used for the sensitivity analysis.

is the second major parameters, while it is the tunnel spacing for the peak rock temperature. One interesting fact is that the main effect of buffer conductivity on the peak rock temperature is very small. That means the variation of buffer thermal conductivity does not consistently increase or decrease the peak rock temperature. The weakest parameters are the thermal conductivity of backfill and EDZ. Even though the effect of backfill and EDZ is insignificant in the sensitivity analysis, it should be kept in mind that the possible variation of the properties in actual situation is much larger than the variation of the other design parameters and thus the actual effect can be more significant.

4. Application of neural network

4.1 Backpropagation

Since the theoretical basis of neural network was developed in 1943 by the McCulloch and Pitts, various techniques including Backpropagation (BP), ART, Hopfield, and etc. could be developed. Many researchers applied the technique for different purposes, mainly for noise reduction, pattern recognition, performance prediction, and optimization (Lawrence, 1993). In this study, BP was used for the prediction of temperature around an underground repository.

BP is a multi-layer feed-forward network that uses a supervised learning method in which an error signal is fed back through the network and changes network values to correct the error and to prevent the same error from happening again (Lawrence, 1993). A theoretical foundation of backpropagation can be found in Rumelhart et al. (1988). It is one of the most commonly used models because it provides a mathematical explanation of the dynamics of learning and has proved to be consistent and reliable. BP is suitable for the analysis of temperature distribution around an underground repository, which is influenced by many parameters and it is not easy to identify an equation adequate for explaining the complex relationship between the parameters and the temperature distribution.

In BP network, input, hidden, and output layers are interconnected and exchange information from one layer to the other. Fig. 5 shows the architecture of the three-layer BP used in this study. Seven input nodes and two output nodes are for the seven input parameters and two resulted temperatures in the sensitivity analysis. There is no formula to determine how many hidden neurons are best for a network, because it is largely dependent upon the complexity of the problem being solved. One rule of thumb is to use the average of the number of inputs and the number of the output neurons (Lawrence, 1993). In this study, therefore, 4 hidden nodes were used.

4.2 Training and testing of neural network

The buffer and rock temperatures from 64 cases were applied for training of the neural network. As shown in Fig. 6, the neural network can fit the temperatures almost exactly after training. In order to check the reliability of the trained network, the network was tested using extra 30 cases with randomly selected input parameters. Among them, the input parameters for 20 cases were randomly chosen in the ±10%

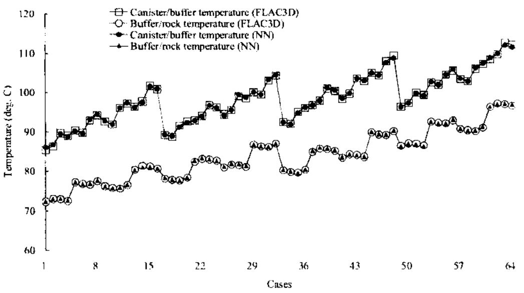

Fig. 6. Training result of the neural network.

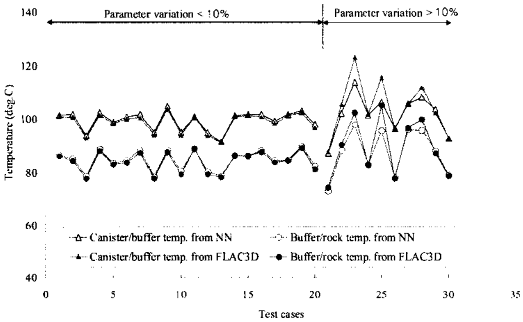

Fig. 7. Testing result of the neural network.

ranges from the reference values as for the sensitivity analysis, while the parameters for the other 10 cases were chosen in larger than ±10% ranges to check whether the trained network has the capability of extrapolation. Fig. 7 shows the testing result. When the parameter variation is less than ±10% from the reference values, the neural network could predict precisely with about 1% error range. With a higher variation of the parameters than ±10%, the prediction accuracy was significantly dropped. From this, it is possible to conclude that the trained neural network does not have the capacity of extrapolation.

4.3 Prediction

The tested neural network was used for a statistical approach on the prediction of the peak temperatures at buffer and rock. Since the calculation time of the temperatures from the network is extremely short compared to that of three-dimensional codes, it was possible to run 1,000 cases with randomly chosen input parameters. Fig. 8 shows the buffer and rock temperatures calculated from the neural network. The influence of

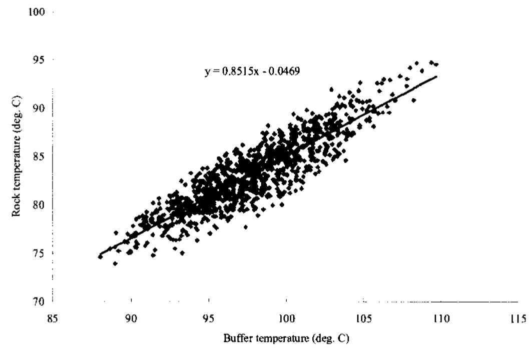

Fig. 8. The relationship between the buffer and rock temperatures from the 1,000 cases with randomly chosen input parameters.

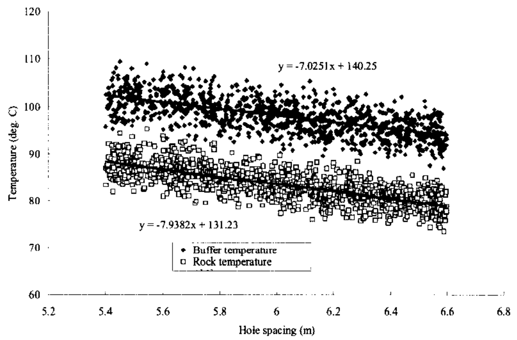

Fig. 9. The relationship between the temperature and hole spacing from the 1,000 cases with different input parameters.

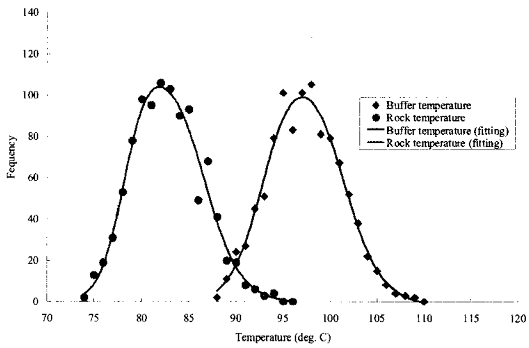

Fig. 10. The distribution of buffer and rock temperatures for 1,000 randomly chosen input parameters.

hole spacing was plotted in Fig. 9. It is possible to observe that the temperatures decrease almost linearly with increase of hole spacing.

The distribution of peak buffer and rock temperatures from 1,000 cases is plotted in Fig. 10. Both show normal distributions with the standard deviation of 3.82 and 3.67°C, respectively. In the case of rock temperature, the peak temperature varies from 74 to 96°C depending on the combination of input parameters, which vary in ±10% range. The buffer temperature varies from 88 to 110°C. Even though the peak buffer temperature with reference design parameters is lower than 100°C, the combination of the parameters with ±10% variation can result over 100°C.

4.4 Parameter adjustment for changing 1deg. C

With the trained neural network, it was possible to estimate the required adjustment of input parameters for changing the buffer and rock temperatures for a certain degree. In order to do that, each input parameter was randomly chosen within ±10% variation, while the other parameters were fixed as the reference values. Fig. 11 shows the predicted temperatures from the neural network for 100 different tunnel spacings. Similarly the following linear equations could be determined for the other parameters;

a. Hole spacing

$$T_{buffer} = -6.6354 \times Hole\ spacing(m) + 137.74 \quad (3)$$

$$T_{rock} = -7.6354 \times Hole\ spacing(m) + 126.95 \quad (4)$$

b. Tunnel spacing

$$T_{buffer} = -0.4385 \times Tunnel\ spacing(m) + 115.42 \quad (5)$$

$$T_{rock} = -0.7711 \times Tunnel\ spacing(m) + 114.26 \quad (6)$$

c. Cooling time

$$T_{buffer} = -0.9181 \times Cooling\ time(year) + 134.59 \quad (7)$$

$$T_{rock} = -0.443 \times Cooling\ Time(year) + 101.12 \quad (8)$$

d. Rock conductivity

$$T_{buffer} = -10.281 \times Rock\ Cond.(W/m^cK) + 123.55 \quad (9)$$

$$T_{rock} = -10.135 \times Rock\ Cond.(W/m^cK) + 108.74 \quad (10)$$

e. Buffer conductivity

$$T_{buffer} = -20.06 \times Buffer\ Cond.(W/m^cK) + 117.92 \quad (11)$$

$$T_{rock} = -0.3543 \times Buffer\ Cond.(W/m^cK) + 83.044 \quad (12)$$

f. Backfill conductivity

$$T_{buffer} = -0.8313 \times Backfill\ Cond.(W/m^cK) + 99.49 \quad (13)$$

$$T_{rock} = -0.5085 \times Backfill\ Cond.(W/m^cK) + 84.408 \quad (14)$$

g. EDZ conductivity

$$T_{buffer} = -1.4069 \times EDZ\ Cond.(W/m^cK) + 102.75 \quad (15)$$

$$T_{rock} = -0.8324 \times EDZ\ Cond.(W/m^cK) + 86.303 \quad (16)$$

From the linear relationship, the required change of each parameter in order to reduce the buffer and rock temperature 1°C can be calculated from the slope of the lines. Table 2 lists the results for the input parameters. It is possible to conclude that a 1.3 m

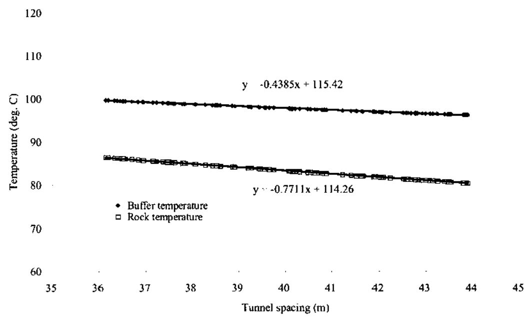

Fig. 11. The relationship between the buffer and rock temperatures and the tunnel spacing.

Table 2. Required change to decrease the buffer and rock temperatures of 1°C.

Parameter	Hole spacing	Tunnel spacing	Cooling time	Rock T.C.	Buffer T.C.	Backfill T.C.	EDZ T.C.
Unit	m	m	year	w/m°K	w/m°K	w/m°K	w/m°K
Buffer Temperature	0.15	2.28	1.09	0.10	0.05	1.20	0.71
Rock Temperature	0.14	1.30	2.26	0.10	2.82	1.97	1.20

longer tunnel spacing or a longer cooling time of 2.26 years is required to decrease the rock temperature for 1°C.

5. Conclusions

The prediction of temperature distribution around an underground HLW repository is important for the design as well as the safety assessment. In this study, a sensitivity analysis for 7 major parameters including (a) deposition hole spacing; (b) tunnel spacing; (c) cooling time; (d) thermal conductivities of rock; (e) thermal conductivities of buffer; (f) thermal conductivities of backfill; and (g) thermal conductivities of EDZ was carried out using FLAC3D. Totally 64 cases were calculated with ±10% variation of the parameters. From the sensitivity analysis, it was possible to determine the relative effect of the parameters on the peak temperatures at buffer and rock. It was found that the effects of hole spacing, tunnel spacing, cooling time and rock thermal conductivity were more significant than the other parameters, when the parameters varied ±10% from their reference values. In order to apply the result, it is required to consider the possible variation in actual condition. For instance, even though the effect of EDZ, with ±10% variation is insignificant, it's effect will be increased with larger variation in actual rock condition.

For the statistical prediction of temperature distribution, it was required to suggest a faster calculation technique than the three-dimensional computer code. In this study, a neural network, backpropagation, was applied to the statistical prediction of the temperatures. After training of a neural network with the calculated temperatures from the 64 cases, the reliability of the trained network was tested with another 30 cases with randomly chosen input parameters. From the testing, it was found that when the parameter variation is within ±10%, the prediction from the network was accurate with about 1% error. Because of that, the input parameters of the 1,000 cases for the statistical prediction of buffer and rock temperatures were randomly chosen within ±10% range. It was possible to observe that the buffer and rock temperatures showed normal distribution with means of 98°C and 83.9°C and the standard deviation of 3.82°C and 3.67°C, respectively. Using the neural network, it was also possible to estimate the required change in design parameters for reducing the buffer and rock temperature for 1°C. The required adjustments of the parameters for decreasing buffer temperature for 1°C are as following:

(a) Deposition hole spacing : +0.15 m
(b) Tunnel spacing : +2.28 m
(c) Cooling time : +1.09 year
(d) Thermal conductivity of rock : +0.1 W/m°K
(e) Thermal conductivity of buffer : +0.05 W/m°K
(f) Thermal conductivity of backfill: +1.2 W/m°K
(g) Thermal conductivity of EDZ: +0.71 W/m°K

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