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A Study on the Improvement of Scaling Factor Determination Using Artificial Neural Network

인공신경망 이론을 이용한 척도인자 결정방법의 향상방안에 관한 연구

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Abstract

Final disposal of radioactive waste generated from Nuclear Power Plant (NPP) requires the detailed information about the characteristics and the quantities of radionuclides in waste package. Most of these radionuclides are difficult to measure and expensive to assay. Thus it is suggested to the indirect method by which the concentration of the Difficult-to-Measure (DTM) nuclide is estimated using the correlations of concentration - it is called the scaling factor - between Easy-to-Measure (Key) nuclides and DTM nuclides with the measured concentration of the Key nuclide. In general, the scaling factor is determined by the log mean average (LMA) method and the regression method. However, these methods are inadequate to apply to fission product nuclides and some activation product nuclides such as ^{14}C and ^{90}Sr. In this study, the artificial neural network (ANN) method is suggested to improve the conventional SF determination methods - the LMA method and the regression method. The root mean squared errors (RMSE) of the ANN models are compared with those of the conventional SF determination models for ^{14}C and ^{90}Sr in two parts divided by a training part and a validation part. The SF determination models are arranged in the order of RMSEs as the following order: ANN model<Regression model<LMA model. It is, therefore, concluded that the ANN model are better than the conventional SF determination model in some nuclides and can be used as the supplement of LMA and regression model.

Key words : scaling factor, artificial neural network, inventory, LMA, regression

I. Introduction

The final disposal of radioactive waste generated from NPP requires the detailed information about the characteristics and the quantities of radionuclides in waste package. However, the determination of inventory of radioactive waste is accompanied with many problems. Representative sampling is very difficult and results in considerable radiation exposure to a sampling personnel. Besides the quantities of most radionuclides except g decaying nuclides are difficult to detect and expensive to assay. Thus it is suggested to the indirect method by which the concentration of DTM nuclides is estimated using the correlations of the concentration between Key nuclides and DTM nuclides with the measured concentration of the Key nuclides.

In general, the scaling factor is determined by statistical processing using large amount of sample data obtained from radiochemical analysis. In this study, the data in EPRI NP-4037 is used [1]. The conventional methods for data processing to determine scaling factor are LMA and regression. It is known that these methods are adequate to apply to most corrosion product nuclides. However, in case of fission product nuclides and some corrosion product nuclides, the predicted values are not well matched with the measured values. It is known that the conventional methods are inadequate to apply to ^{14}C and ^{90}Sr.

In this study, the ANN models for ^{14}C and ^{90}Sr are compared with the LMA models and the regression model to evaluate the applicability of the ANN model in SF determination.

II. Conventional SF Determination Method

The conventional SF determination methods which are used largely are the LMA and the regression. The LMA is easy to establish a model and to understand it without any plots because the model has one parameter. However, it is weak to describe the complex relationship between a response variable and an input variable, and only one Key nuclide can be used as input data for the predicted value of the activity of DTM nuclides. The modeling equation of the LMA model is expressed as the following formula.

$$A_{predicted_i} = A_{SF} \times A_{Key_i} \quad \text{----------(1)}$$

$$A_{sf} = e\left(\frac{\sum_{i=1}^{n} Ln(SF)_i}{N}\right) = e\left(\frac{\sum_{i=1}^{N} Ln(\frac{A_{DTM_i}}{A_{Key_i}})}{N}\right) \quad \text{----------(2)}$$

$A_{predicted_i}$: i^{th} predicted value of the activity of DTM nuclide

A_{DTM_i} : i^{th} measured value of the activity of DTM nuclide

A_{Key_i} : i^{th} value of the activity of Key nuclide

A_{SF} : log mean average of the SFs in the data set

$(SF)_i$: i^{th} value of the scaling factor in the data set : (A_{DTM_i}/A_{Key_i})

N : number of values in the set

The formations of regression model are various. In this study, a multiple intrinsically linear model is used [2]. The regression is easy to understand the effect of each variable and strong to describe the complex relationship between a response variable and input variables. However, it is necessary to predict the rough model before establishing a correct model. Besides this model originally is linear, it is weak to describe non-linear model. The modeling equation of the regression model is expressed as the following formula.

$$Ln(A_{predicted_i}) = \beta_O + \beta_1 Ln(A_{Key_{1i}}) + \beta_2 Ln(A_{Key_{2i}}) \quad \text{———————} (3)$$

$A_{predicted_i}$: ith predicted value of the activity of DTM nuclide

$A_{Key_{1i}}$: ith value of the activity of the 1st Key nuclide

$A_{Key_{2i}}$: ith value of the activity of the 2nd Key nuclide

$\beta_O, \beta_1, \beta_2$: parameters to describe the regression models

Ⅲ. Artificial Neural Network

ANN is a method of data processing. It is inspired by the structure of the brain and utilizes a parallel processing structure [3]. In general, ANN is used to solve complex non-linear problems. ANN is divided by various classifications. Multilayer perceptron (MLP) is widely used in area of data processing. The basic structure of MLP is shown in Figure 1. ANN cannot be used until it is trained. The purpose of training is to determine the unique weighting factor associated with each connection. Initially, weighting factors are assigned arbitrary values. The weighting factors change during the training phase. Once training is over, the weighting factor becomes fixed. In Figure 1, the inputs are multiplied by weighting factors and the products are summed. The sum of the products changes into a non-linear shape by a transfer function. The former sum is a combination function and the latter transfer function is an activation function. A combination function and activation function are very important factors to determine the characteristic of ANN with the number of hidden layers and hidden nodes. In this study, a linear function is used as a combination function and hyperbolic tangent sigmoid function as an activation function.

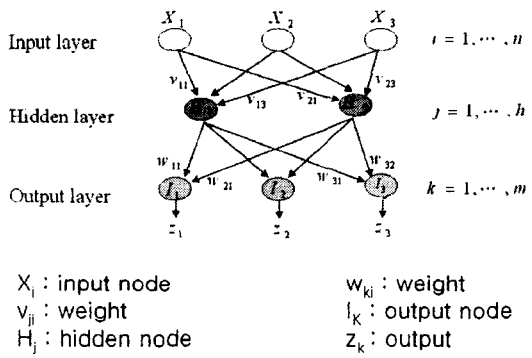

Figure 1. Structure of MLP

Ⅳ. Application of SF determination

The ANN models for ^{14}C and ^{90}Sr are compared with the LMA model and the regression model. ^{60}Co and ^{137}Cs are used as Key nuclides and the data in EPRI NP-4037 as raw data for the assessment. The assessment of models is executed in the

two parts divided by a training part and a validation part [4, 5]. 80% of the raw data are used for training and 20% of them for validation. The summary of the models used for the comparison is shown in Table I.

The RMSE is used as the method for the assessment of models. The RMSE represents the difference between the predicted values of the activities of DTM nuclides and the measured values of them for each model. Therefore, as the RMSE of a model is getting smaller, the model is good for the SF determination. The RMSE is shown by Equation (4).

$$RMSE = \sqrt{\frac{\sum_{i=1}^{N} (Ln(A_{predicted_i}) - Ln(A_{measured_i}))^2}{N}}$$

--(4)

$A_{predicted_i}$: i[th] predicted value in a data set

$A_{measured_i}$: i[th] measured value in a data set

N : number of values in the set

V. Results and Discussion

Figure 2 shows the scatter plot between the predicted values for the concentration of ^{14}C and the measured values for each model in a training part and Figure 3 does in a validation part. Figure 4 shows the comparison of RMSE of each model for ^{14}C. Figure 2~4 show that in the training part of ^{14}C, the ANN model having 6 hidden nodes in 1[st] hidden layer and 4 hidden nodes in 2[nd] one results in the best predicted values and in the validation part, the ANN model having the 10 hidden nodes in one hidden layer does.

Table I. Summary of LMA, regression and ANN models

Log mean average	Artificial neural network
■ Classification by Stream	■ Model : Multilayer Perceptron
■ Key nuclides : ^{60}Co, ^{137}Cs (2 models)	■ Combination function : Linear function
■ Each SF for each stream	■ Activation function: Hyperbolic tangent sigmoid
Regression	■ Input node(3) : Stream No., ^{60}Co, ^{137}Cs
■ Multiple Linear Intrinsically Regression (1 model)	■ Hidden layer :
■ Three dependent variable : ^{60}Co, ^{137}Cs, Stream No.	- 10 hidden nodes in one hidden layer (1 model)
	- 6 hidden nodes in 1[st] hidden layer and 4 hidden nodes in 2[nd] hidden layer (1 model)
	■ Target node(1): ^{14}C (or ^{90}Sr)

Figure 5 shows the scatter plot between the predicted values for the concentration of ^{90}Sr and the measured values for each model in a training part and Figure 6 does in a validation part. Figure 6 shows the comparison of RMSE for each model. Figure 7 shows the comparison of RMSE of each model for ^{14}C. Figure 5~6 show that in the training part of ^{90}Sr, the ANN model having 10 hidden nodes in one layer results in the best predicted values and in the validation part of ^{90}Sr, the ANN model having 6 hidden nodes in 1st hidden layer and 4 hidden nodes in 2nd one does.

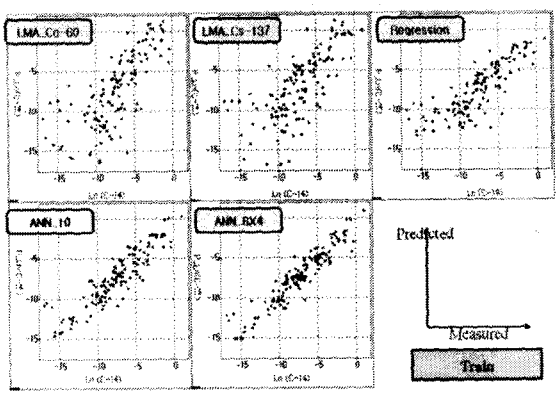

Figure 2. Scatter plot between the predicted values for concentration of ^{14}C and the measured values for each model in a training part

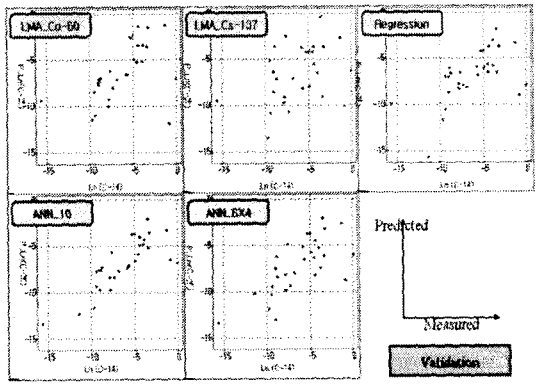

Figure 3. Scatter plot between the predicted values for concentration of ^{14}C and the measured values for each model in a validation part

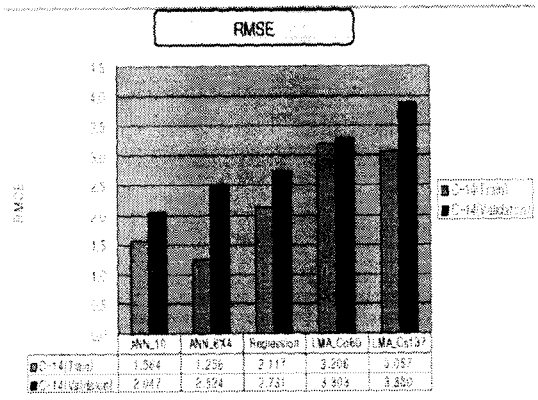

Figure 4. RMSE of each model for ^{14}C

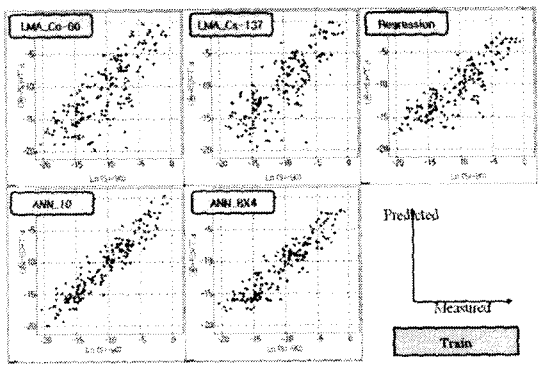

Figure 5. Scatter plot between the predicted values for the concentration of ^{90}Sr and the measured values for each model in a training part

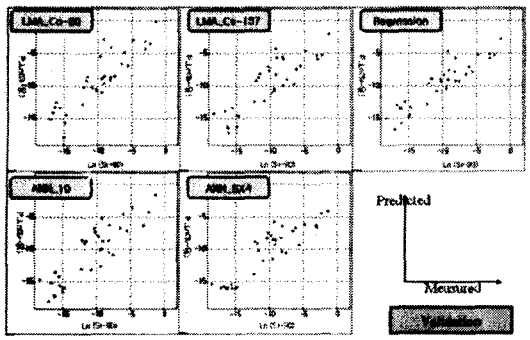

Figure 6. Scatter plot between the predicted values for the concentration of ^{90}Sr and the measured values for each model in a validation part

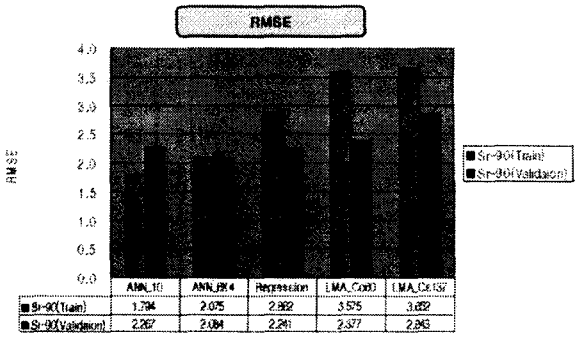

Figure 7. RMSE of each model for ^{90}Sr

VI. Concluded Remarks

In this study, the ANN method is compared with the conventional SF determination method for the improved SF determination. The SF determination models are arranged in the order of RMSEs as the following order: ANN model<Regression model<LMA model. Especially, the LMA model is inadequate to determine SF for the nuclides having the complex relationship between Key nuclides and DTM nuclides such as ^{14}C and ^{90}Sr by its simple modeling equation. It is concluded that the ANN method is superior to the conventional SF determination methods in some nuclides and can be used as the supplement of the LMA model and the regression model.

VII. Acknowledgments

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VIII. References

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