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A Study on Improvement of Scaling Factor Prediction Using Artificial Neural Network

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Abstract

Final disposal of radioactive waste generated from Nuclear Power Plant (NPP) requires the detailed knowledge of the natures and quantities of radionuclides in waste package. Many of these radionuclides are difficult to measure and expensive to assay. Thus it is suggested to the indirect method by which the concentrations of DTM (Difficult-to-Measure) nuclide is decided using the relation of concentrations (Scaling Factor) between Key (Easy-to-Measure) nuclide and DTM nuclide with measured concentrations of Key nuclide. In general, scaling factor is determined by using of log mean average (LMA) and regression. These methods are adequate to apply most corrosion product nuclides. But in case of fission product nuclides and some corrosion product nuclides, the predicted values aren't well matched with the original values. In this study, the models using artificial neural network (ANN) for C-14 and Sr-90 are compared with those using LMA and regression. The assessment of models is executed in the two parts divided by a training part and a validation part. For all of two nuclides in the training part, the predicted values using ANN are well matched with the measured values compared with those using LMA and regression. In the validation part, the accuracy of the predicted values using ANN is better than that using LMA and is similar to or better than that using regression. It is concluded that the predicted values using ANN model are better than those using conventional model in some nuclides and ANN model can be used as the complement of LMA and regression model.

1. Introduction

Final disposal of radioactive waste generated from Nuclear Power Plant(NPP) requires the detailed knowledge of the natures and quantities of radionuclides in waste package. But the determination of inventory of radioactive waste is accompanied with a number of problems. Representative sampling is very difficult or result in considerable radiation exposure to sampling personnel. Besides the quantities of most radionuclides except γ decaying nuclides are difficult to detect and expensive to assay. Thus it is suggested to the indirect method by which the concentrations of DTM(Difficult-to-Measure) nuclide is decided using the relation of concentrations (Scaling Factor) between Key (Easy-to-Measure) nuclide and DTM nuclide with measured concentrations of Key nuclide.

In general, scaling factor is determined by statistical processing using large amount of sample data gotten through radiochemical analysis. In this study, the data in EPRI-4037 is used [1]. The conventional methods for data processing to determine scaling factor are log mean average (LMA) and

regression. It is known that these methods are adequate to apply most corrosion product nuclides. But in case of fission product nuclides and some corrosion product nuclides, the predicted values aren't well matched with the original values. It is known that the conventional methods are inadequate to apply for C-14 and Sr-90.

In this study, the models using artificial neural network (ANN) for C-14 and Sr-90 are compared with those using LMA and regression. As a result, the possibility of application of ANN for SF determination method is assessed.

2. Conventional SF Determination Method

The conventional SF determination methods which are used largely are LMA and regression. LMA is easy to establish and to understand because the model has one parameter. But it is difficult to describe. The modeling equation of LMA 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 kinds of regression model are various. In this study, a multiple intrinsically linear model is used [2]. Regression is easy to understand the effect of each variable and to describe. But it is necessary to predict the rough model before establishing the model. The modeling equation of regression is expressed as the following formula.

$$Ln(A_{predicted\_i}) = \beta_0 + \beta_1 Ln(A_{Key\_1i}) + \beta_2 Ln(A_{Key\_2i}) \quad \text{----------(3)}$$

$A_{predicted\_i}$: 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_1i} : i^{th} value of the activity of the 1^{st} Key nuclide
A_{key_2i} : i^{th} value of the activity of the 2^{nd} Key nuclide
β_0, β_1, β_2 : parameters to describe the regression models

3. Artificial Neural Network

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 an 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 a hyperbolic tangent sigmoid function as an activation function.

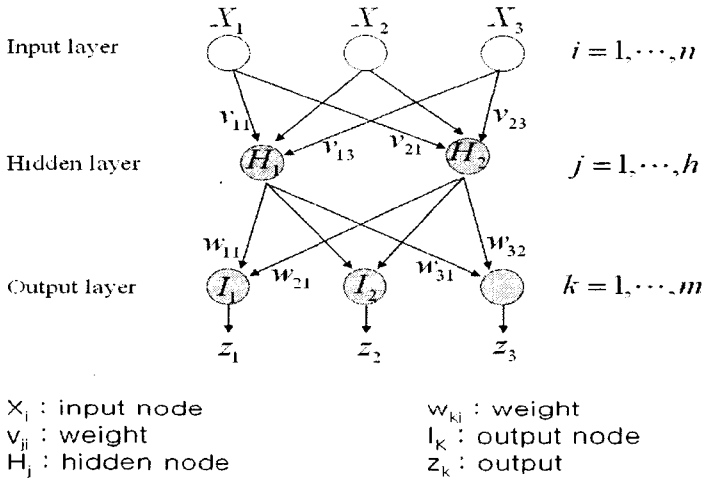

Figure 1. the structure of MLP

4. Application of SF determination

The models using ANN for C-14 and Sr-90 are compared with those using LMA and regression. Co-60 and Cs-137 are used as Key nuclides and the data in EPRI-4047 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 is used for training and 20% of them for validation. The summary of the models used for the comparison are shown in Table I.

Table I. the summary of LMA, regression and ANN models

Log mean average ■ Classification by Stream ■ Key nuclides : Co-60, Cs-137 (2 models) ■ Each SF for each stream	Artificial neural network ■ Model : Multilayer Perceptron ■ Combination function : Linear function ■ Activation function : Hyperbolic Tangent sigmoid ■ Input node(3) : Stream No., Co-60, Cs-137 ■ Hidden layer : 10, 6X4 (2 models) ■ Target node(1): C-14 (or Sr-90)
Regression ■ Multiple Linear Intrinsically Regression (1 models) ■ Three dependent variable : Co-60, Cs-137, Stream No.	

The root mean squared error (RMSE) is used as the method for the assessment of models. RMSE represents the difference between predicted values and measured values for each model. RMSE is shown by Equation (4).

$$RMSE = \sqrt{\frac{\sum_{i=1}^{N}\{Ln(A_{PDi}) - Ln(A_{MSi})\}^2}{N}} \quad \text{----------(4)}$$

A_{PDi} : i^{th} predicted value in a data set A_{MSi} : i^{th} measured value in a data set
N : number of values in the set

4.1 C-14

Figure 2 shows the scatter plot between the predicted values for the concentration of C-14 and the measured values for each model in a training part and Figure 3 shows in a validation part.

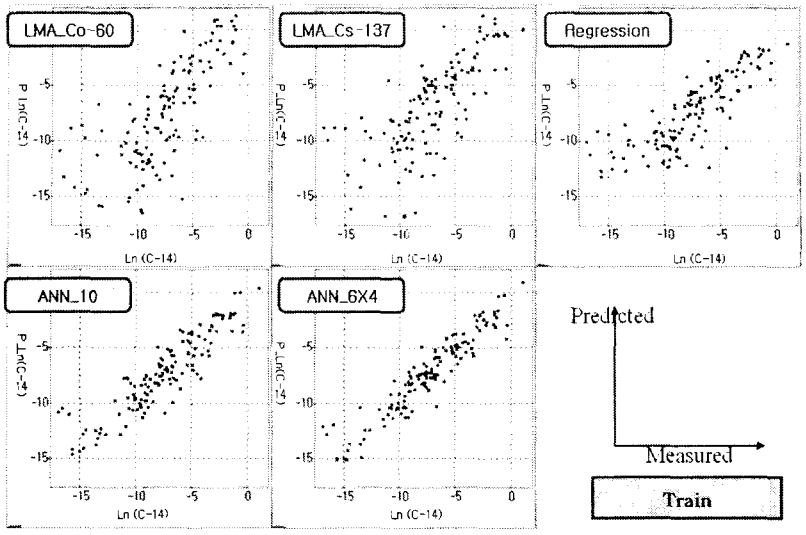

Figure 2. the scatter plot between the predicted values for concentration of C-14 and the measured values for each model in a training part

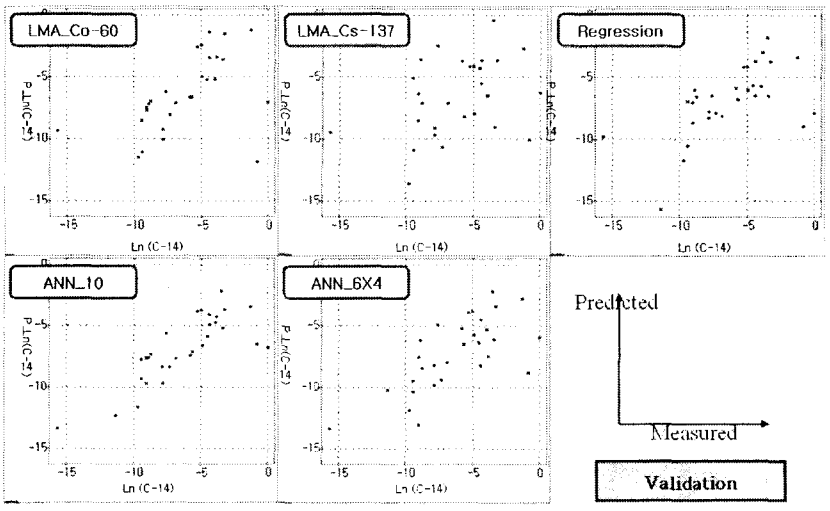

Figure 3. the scatter plot between the predicted values for concentration of C-14 and the measured values for each model in a validation part

4.2 Sr-90

Figure 4 shows the scatter plot between the predicted values for the concentration of Sr-90 and the measured values for each model in a training part and Figure 5 shows in a validation part.

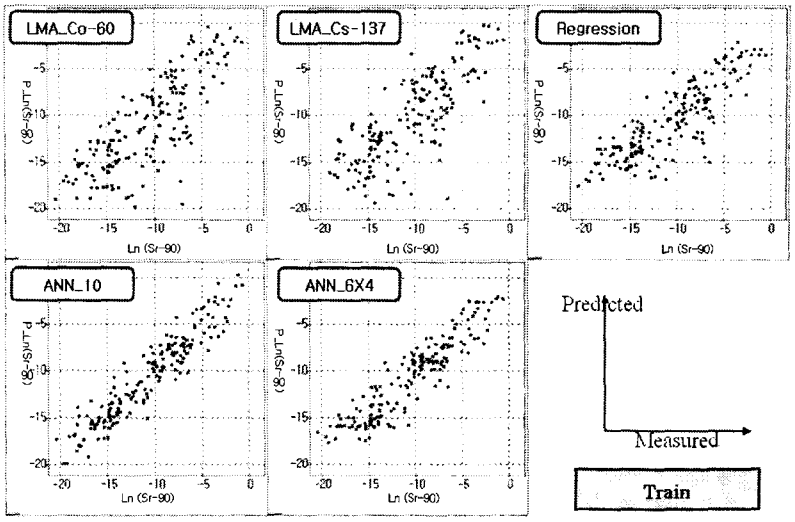

Figure 4. the scatter plot between the predicted values for the concentration of Sr-90 and the measured values for each model in a training part

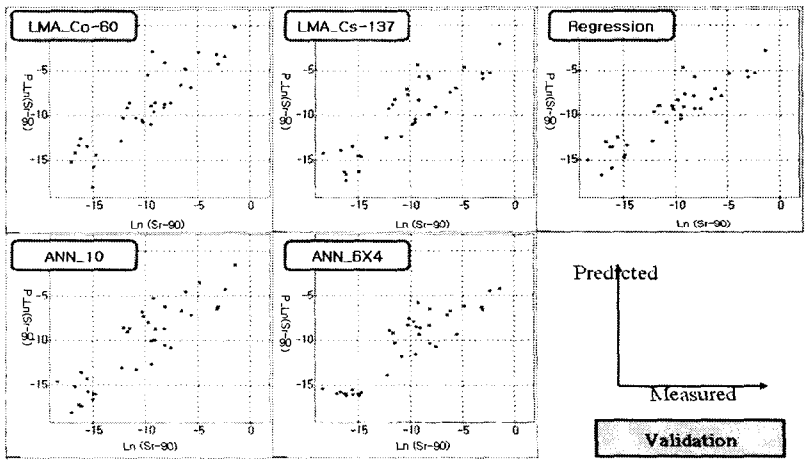

Figure 5. the scatter plot between the predicted values for the concentration of Sr-90 and the measured values for each model in a validation part

5. Results

In the training part of C-14, the model using ANN of which the hidden layer consists of 6 X 4 hidden nodes results in the best predicted values and in the validation part, the model using ANN of which the hidden layer consists of 10 hidden nodes does. In the training part of Sr-90, the model using ANN of which the hidden layer consists of 10 hidden nodes results in the best predicted values and in the validation part of Sr-90, the model using ANN of which the hidden layer consists of 6X4 hidden nodes does. Figure 6 compares the RMSE for each model.

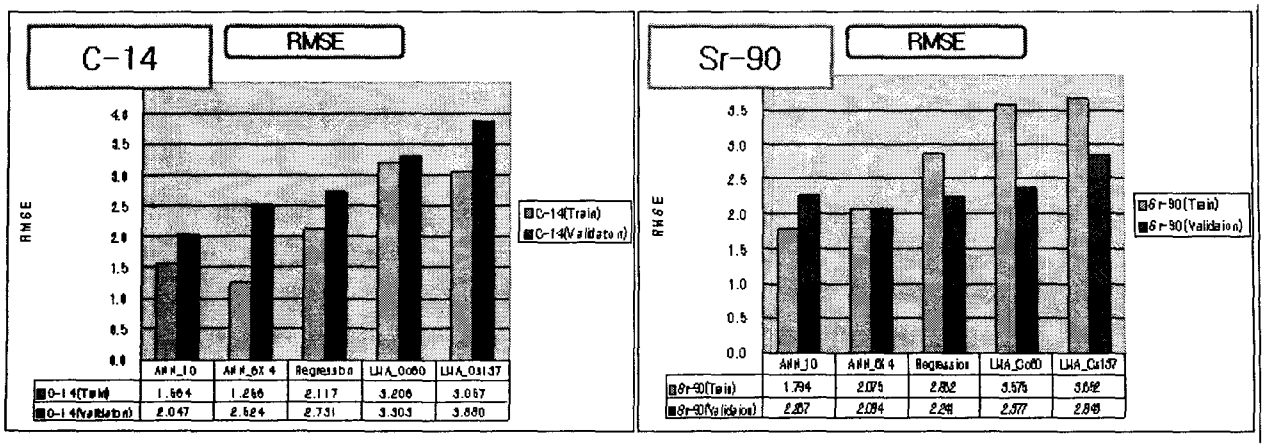

Figure 6. the RMSE for each model

6. Conclusion

For all of two nuclides in a training part, the predicted values using ANN are well matched with the measured values compared with those using LMA and regression. In a validation part, the accuracy of the predicted values using ANN is better than that using LMA and is similar to or better than that using regression. It is concluded that the predicted values using ANN model are better than those using conventional model in some nuclides and ANN model can be used as the complement of LMA and regression model.

Acknowledgments

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