Uncertainty Analysis of the LOCA Break Size Prediction Model using GMDH

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Keywords: Group Method of Data Handling (GMDH), Uncertainty Analysis, LOCA (Loss of Coolant Accidents), Prediction of Break Size.

Abstract: When transients or accidents occur in the nuclear power plants, the plant operators and technical staffs are provided with only partial information and faced with a number of signals and alarms. Therefore, providing information such as a break size in case of LOCA is essential to control these events successively. In this paper, in order to predict the LOCA break size, a prediction model was developed by using group method of data handling (GMDH) algorithm, and we have conducted its uncertainty analysis. The proposed prediction model was verified using the acquired data from the OPR1000 nuclear power plant.

1 INTRODUCTION

After the Fukushima nuclear power plant accident, the public concern about the safety of nuclear power plants (NPPs) has been growing.

If accidents or transients occur in NPPs, it is important to check short time trend of major parameters. However, if it is a severe accident, it is very difficult to find out the initial event, since the plant operators and technical staffs are offered with only partial information or not have sufficient time to analyze the accident in the urgent situation. During the accident, operators and technical staffs will be faced with a number of signals and alarms. Therefore, providing information such as a break size is important to control this event successively.

This study aims to predict the break size of loss of coolant accidents (LOCA) and steam generator tube rupture (SGTR) which may lead to severe accident conditions by applying a group method of data handling (GMDH). Additionally, the accuracy of the proposed prediction model is verified by its uncertainty analysis.

2 PREDICTION OF THE LOCA BREAK SIZE USING GMDH

In order to solve the system problem such as control, monitoring, prediction, diagnosis and so on, a lot of mathematical methods have been studied.

The GMDH method is one of them. The GMDH method which is one of the data-driven models such as ANN (Artificial Neural Network) can be used for LOCA break size prediction in this paper. Data-driven models have many advantages of easy implementation and accuracy, and famous for superior capability in modelling complex systems.

In this paper, the GMDH method has been used to develop a model for LOCA break size prediction.

2.1 Basic GMDH Algorithm

The GMDH algorithm is a way of finding a function that well expresses a dependent variable from independent variables. This method can find a correlation in the data automatically to improve the prediction accuracy and select the optimal structure of the model. The GMDH algorithm is similar to multiple regression model, but it uses the data structure. The data set is divided into three subsets. The reason of dividing is to prevent over-fitting and maintain model regularization through cross-validation. Figure 1 shows the data structure of the GMDH algorithm.

The GMDH model uses a self-organizing algorithm that can select nonlinear forms of the basic inputs. Figure 2 shows the branch architecture of the GMDH model. It shows the branch structure of the GMDH model to start with the basic inputs in the first step.

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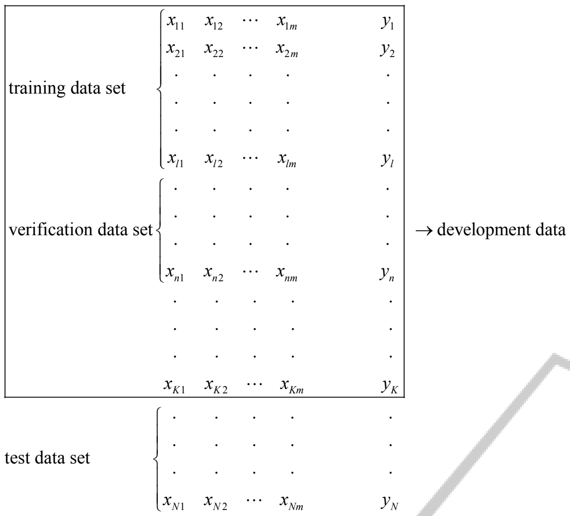

Figure 1: GMDH data structure.

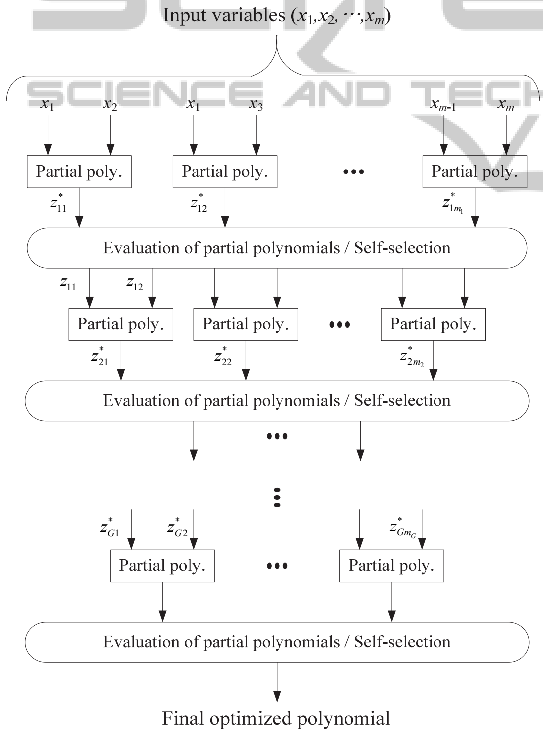

Figure 2: GMDH structure.

The original GMDH method employed the following general form at each level of the successive approximation:

$$y = f(x_i, x_j) = A + Bx_i + Cx_j + Dx_i^2 + Ex_j^2 + Fx_i x_j \qquad (1)$$

The coefficient parameters of the reference function which is written above such as $A, B, ..., F$ can be obtained by using a least square method in an arbitrary pair (x_i, x_j) from independent variables $\mathbf{x} = (x_1, x_2, \cdots, x_m)$. This method takes a form of hierarchical polynomial regression network to model various complex input-output relationships. However, more complicated function forms can be used such as ratio terms (x_i / x_j), trigonometric terms ($\sin(cx)$, $\cos(cx)$), exponential terms ($\exp(-cx)$) and so on in accordance with complexity of the system. The GMDH algorithm uses the Kolmogorov-Gabor form of a high-order polynomial. The Kolmogorov-Gabor form that is called as Ivakhnenko polynomial can be expressed as follows:

$$y = a_0 + \sum_{i=1}^{m} a_i x_i + \sum_{i=1}^{m}\sum_{j=1}^{m} a_{ij} x_i x_j + \sum_{i=1}^{m}\sum_{j=1}^{m}\sum_{k=1}^{m} a_{ijk} x_i x_j x_k \ldots \qquad (2)$$

where $\mathbf{x} = (x_1, x_2, \cdots, x_m)$ is an input vector and $\mathbf{a} = (a_0, a_i, a_{ij}, a_{ijk,} \cdots)$ is a coefficient vector that is a weight vector of Kolmogorov-Gabor polynomial. The GMDH algorithm can determine the structure of the model and also calculate the system output of the most important input simultaneously. This uses the composition of the lower-order polynomials mentioned above, which means that the GMDH algorithm amalgamates lower order polynomials at each generation to reach the subsequent generation. This process continues until the GMDH model begins to show over-fitting in training or exceeds the maximum calculation time. If an evaluation value (R) is greater than a reference value, the regression equation is fallen behind. Otherwise, the regression equation is survived. The survived regression equation value is used as a training data of the new generation. This process is conducted about all possible pairs of independent variables. The descendant with the smallest evaluation value in the evaluation of this generation is selected as the optimum fit. If the smallest evaluation value of the current generation is smaller than that of the previous generation, the above process is performed repeatedly. When over-fitting of the evaluation ($R_{\min}^{G}$) value is found through alternation of generation, the process is stopped. That is, if the smallest evaluation value of the current generation is larger than that of the previous generation, the process is stopped.

As shown in Figure 3, if over-fitting is found, the process of the algorithm is stopped and the optimum fit of the previous generation is selected as the optmized model that predicts the LOCA size.

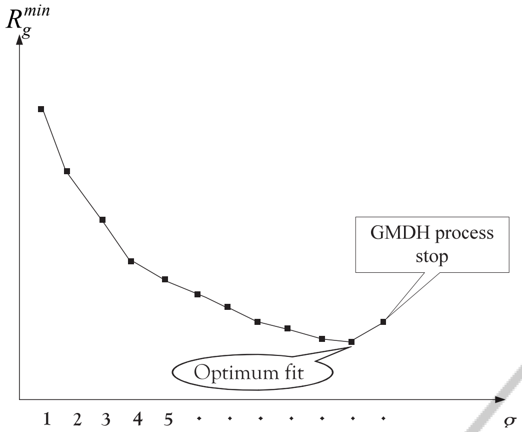

Figure 3: Value of each generation.

2.2 Main Implementation Steps

The GMDH algorithm generates and tests all input-output combinations. Each element in the system that is indicated as a rectangle box in Figure 2 executes a function of two inputs. The coefficient parameters of Eq. (2) are decided by using a normal least square method, and the variables of the elements are calculated. A threshold value for comparison with the evaluation value in each generation decides whether the outputs of the elements in a generation are acceptable. The output of an element is eliminated in a current generation when the result is larger than the threshold value. Those variables or elements that are useful for predicting the proper output are used at the next generation. The generations are repeated until the satisfactory results are obtained. This process is similar to Darwin's theory. The detailed main implementation steps are given below.

First step, construct each of input and output variable or data of the system. The data structure is modeled and divided into the training and checking data sets, and preprocess the data to normalize them.

Second step, choose the external inputs to the GMDH network. Calculate the regression polynomial parameters for each pair of input variables involved in the training data set using the least square method. Calculate the $m(m-1)/2$ high-order variables in place of the original input variables $x_1, x_2, \cdots, x_m$ in order to predict the output.

Third step, the algorithm designs a group of new variables ($m_g = m_{g-1}(m_{g-1}-1)/2$) in the previous step. Here, m_g is the number of input variables for generation g . A criterion is used to evaluate the new variables in the generation g and is related with the error for the checking data, which is defined as follows:

$$r_j^2 = \frac{\sum_{i=l+1}^{n}\left(y_i - z_{ij}\right)^2}{\sum_{i=l+1}^{n} y_i^2} \quad for \;\; j = 1, 2, \ldots, m_g \tag{3}$$

Last step, when over-fitting is found through checking, the above mentioned process is stopped. If the generation continues, the model will become over-fitted. The polynomial with the minimum error criterion is selected as the final approximate model. Otherwise, the above steps are repeated.

At the end of the GMDH algorithm, regression parameters are stored. The estimated coefficient for the high-order polynomial is determined by tracing back the GMDH structure until it reaches the original variables $x_1, x_2, \cdots, x_m$. As shown in Figure 4, the tree structure with the optimum fit at the top is called an Ivakhnenko Tree.

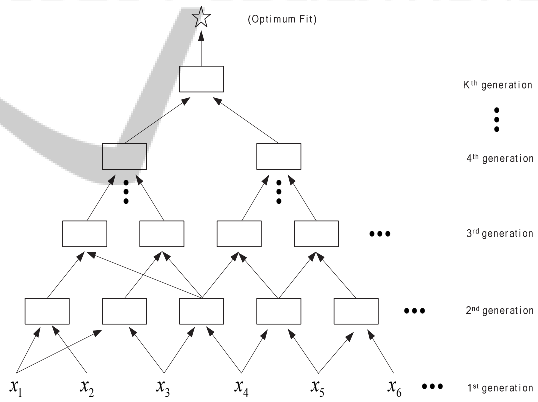

Figure 4: Ivakhnenko tree.

3 UNCERTAINTY ANALYSIS

The data-based model has several sources of uncertainty in the predicted values such as selection of training data, model structure including complexity, and noise in the input and output variables. The data-based model is developed by using a given training data set. Each of the training data set selected from entire data group will generate a different model and have a distribution of predicted values for a given observation data. Furthermore, inappropriate model causes a bias. This paper uses statistical uncertainty analysis methods.

3.1 Statistical Method

The statistical uncertainty analysis generates many bootstrap samples of the training data set and is conducted through training of data-based model parameters. After sampling and training repeatedly, the result of the prediction provides a distribution for output value. In this paper, the bootstrap pairs sampling algorithm, which is one of the statistical methods was used. Figure 5 shows the bootstrap pairs algorithm structure.

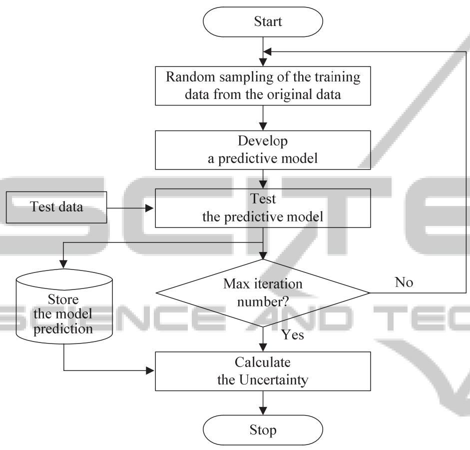

Figure 5: Bootstrap pairs sampling algorithm structure.

The detailed bootstrap pairs sampling algorithm is given below.

First step, generate samples J (the number of bootstrap samples) through sampling with replacement from the development data pool.

Second step, the data-based model is obtained for each bootstrap sample.

Last step, calculate the variance and the bias of an observation data output y_o by using following equation:

$$Var(\hat{y}_0) = \frac{1}{J-1}\sum_{j=1}^{J}\left[\hat{y}_0^j - \overline{\hat{y}}_0\right]^2 \tag{4}$$

where

$$\overline{\hat{y}}_0 = \frac{1}{J}\sum_{j=1}^{J}\hat{y}_0^j$$

$$bias = \left\{\frac{1}{K}\sum_{k=1}^{K}\frac{1}{J}\sum_{j=1}^{J}\left[\hat{y}_k^j - y_k^j\right]^2\right\}^{1/2} \tag{5}$$

The estimate with a 95% confidence for an arbitrary test input x_0 can be expressed as follows:

$$\hat{y}_0 \pm 2\sqrt{Var(\hat{y}_0) + bias^2} = \hat{y}_0 \pm \delta \tag{6}$$

3.2 Application to the LOCA Break Size Prediction

In this paper, the proposed prediction model was verified by applying to a number of numerical simulations of OPR1000 NPPs. The number of 810 accident simulations were conducted using the MAAP4 code to acquire the data. The data were composed of 270 hot-leg LOCA, 270 cold-leg LOCA and 270 SGTR, and were divided into development data and test data. Each accident simulation data is selected into 30 test data, 190 training data and 50 checking data.

Table 1: Performance of the proposed GMDH algorithm.

Event type	Data type	MAX. error (%)	RMS error (%)
Hot-leg LOCA	Training data	25.5019	3.1061
	Verification data	10.4794	2.6101
	Test data	15.8917	3.5650
Cold-leg LOCA	Training data	9.2525	1.9933
	Verification data	16.6147	3.1979
	Test data	8.6985	2.5440
SGTR	Training data	15.3771	2.8586
	Verification data	13.8253	2.7114
	Test data	9.8385	2.6438

Table 1 summarizes the performance results of the proposed GMDH algorithm, and Figure 6-8 shows a result of each prediction interval, calculation errors, and uncertainty analysis. As shown in Figures 6-8, the prediction interval is very small which means that the model is accurate.

4 CONCLUSIONS

In this paper, a prediction model was developed to estimate the LOCA break size of NPPs using the GMDH algorithm. The proposed GMDH model was applied and verified using the acquired real plant data of OPR1000. Additionally, the prediction interval was calculated by using the statistical uncertainty analysis.

As a result of simulation, the performance of the GMDH model was very well. The RMS errors of test data in hot-leg LOCA, cold-leg LOCA and SGTR are 3.5650%, 2.5440% and 2.6438%, respectively. The proposed prediction model of LOCA break size using the GMDH model fits very well.

If the GMDH model is optimized by using a variety of data, it is possible to predict the NPP LOCA size more accurately.

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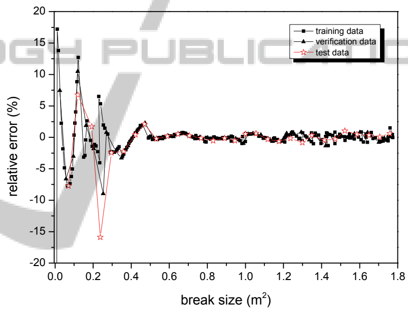
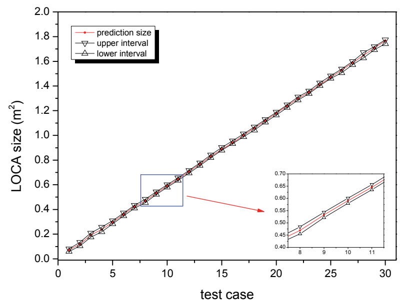
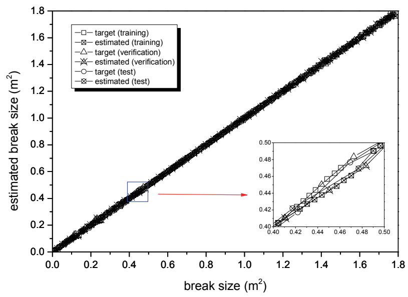


(a) relative error

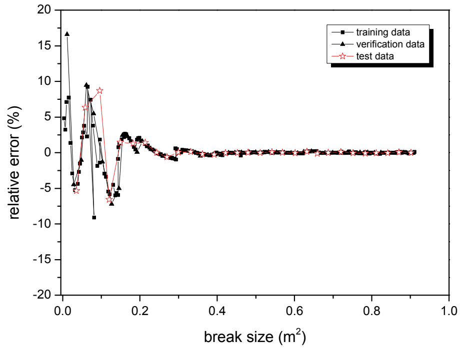


(b) uncertainty analysis

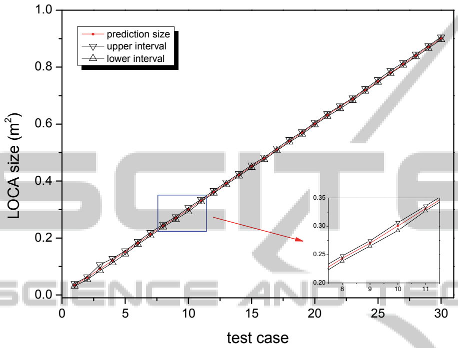


(c) estimated break size

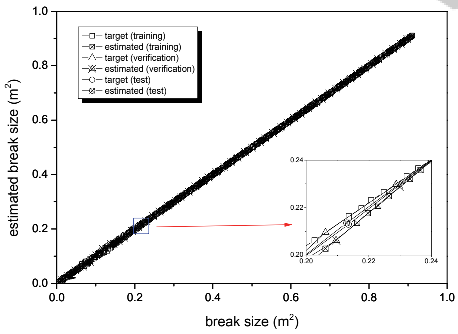
Figure 6: Prediction of hot-leg LOCA break size.



(a) relative error

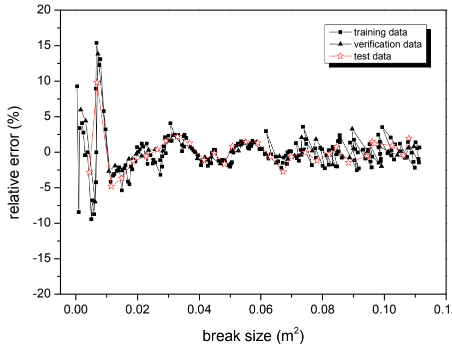


(b) uncertainty analysis

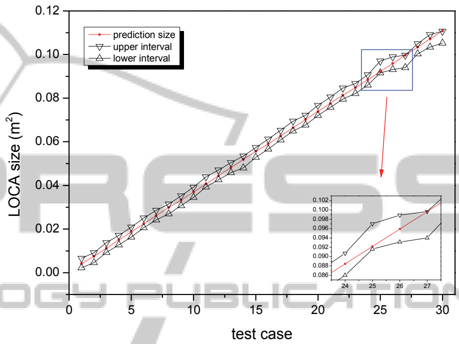


(c) estimated break size

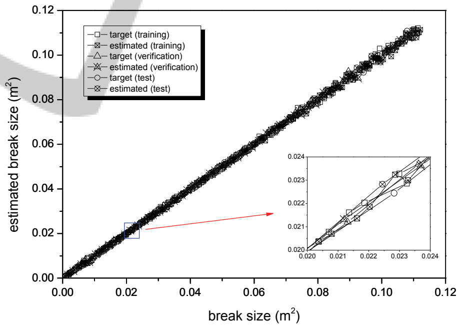
Figure 7: Prediction of cold-leg LOCA break size.



(a) relative error



(b) uncertainty analysis



(c) estimated break size

Figure 8: Prediction of SGTR break size.