Prediction of Major Transient Scenarios for Severe Accidents of Nuclear Power Plants Using GMDH

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1. Introduction

It is important for operators and technical staffs to find out what an initiating event of a severe accident is by observing initial short time trends of major parameters in order to effectively accomplish severe accident management strategies. If they know some time sequences of major severe accident scenarios, they can cope with situations that can lead to the worst situation that plant safety systems do not work appropriately. The present work aims to classify the initiating events which may lead to severe accident conditions such as loss of coolant accidents (LOCA) and steam generator tube rupture (SGTR) by applying a support vector classification (SVC). Also, another objective is to identify the major severe accident scenarios such as core uncovery, core exit temperature (CET) and reactor vessel (RV) failure by using a group method of data handling (GMDH) algorithm of which the inputs are the time-integrated values of important measured signals during a short time interval after reactor scram [1].

The proposed algorithm for the initiating event classification and the major severe accident scenario identification is verified by comparison with the simulation data of the MAAP4 [2] code for the advanced power reactor 1400 (APR1400) developed by Korea Hydro & Nuclear Power company (KHNP).

2. Group Method of Data Handling (GMDH)

2.1 Basic GMDH Algorithm

The GMDH algorithm [3] is the way to find a function that can well express a dependent variable from independent variables. This method uses a data structure similar to that of multiple regression models. The data set can be divided into the training data and test data. The reason of dividing the data set is to prevent over-fitting and maintain model parsimony.

The GMDH uses a self-organizing modeling algorithm with the flexibility of deciding nonlinear forms of the basic inputs $[x_1, x_2, \cdots, x_m]$. Figure 1 shows the branch structure of the GMDH model. It starts with the basic inputs at the first layer and becomes more complex according to the increasing number of layers.

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

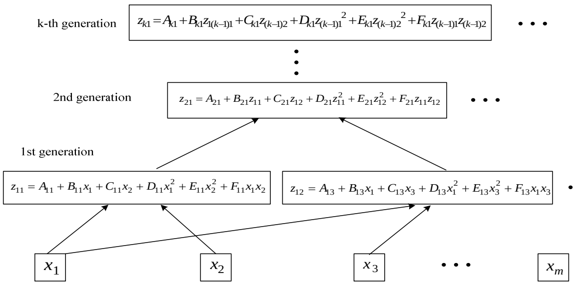

Fig.1 Branch structure of the GMDH model

approximation:

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

The GMDH algorithm employs a high-order polynomial in the Kolmogorov-Gabor form. The Kolmogorov-Gabor (called as Ivakhnenko polynomial) is 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 variable vector and $\mathbf{a} = (a_0, a_i, a_{ij}, a_{ijk,} \cdots)$ is a vector of coefficients or a weight of the Kolmogorov-Gabor polynomial. Components of the input vector $\mathbf{x}$ can be independent variables, functional forms or finite difference terms.

2.2 Training Data Selection

The GMDH algorithm has been developed and improved in many applications. The main steps in its implementation are given below.

The first step is to classify the data. That is, after constructing the input and corresponding output data for GMDH model, it is divided into training and test sets.

The second step is to establish a new variable. The external inputs have to be chosen to the GMDH network. And then calculate regression polynomial parameters for each pair of input variables $\mathbf{x}$ and combined output y in the training sets. Thus least-squares error (LSE) linear regression parameters are calculated.

The next step is to remove the variables which have little contribution. A measure used to evaluate the new variables at each generation is the fractional error defined as:

$$r_j^2 = \frac{\sum_{i=1}^{n} (y_i - z_{ij})^2}{\sum_{i=1}^{n} y_i^2} \quad \text{for } j = 1, 2, \cdots \tag{3}$$

The last step is to take the optimality test. The process above is performed repeatedly until over-fitting is found through cross checking; that is, when the root mean square error (RMSE) of current layer is larger than the last layer. The minimum value of those r_j for generation k is denoted as $R_{\min k}$, if $R_{\min k} > R_{\min}$, then the training and testing processes of the algorithm stop and the polynomial with the minimum value of the error criterion in layer $k-1$ is selected to be the final approximate model. Otherwise, the algorithm moves to the next layer and repeats the above steps.

3. Verification of the Proposed Algorithm

To verify the proposed algorithm, it is essential to acquire the data required to train the SVC and GMDH models from a number of numerical simulations because there is little real LOCA data.

Table 1. Performance of the proposed GMDH

Event type	Scenario time	Data type	RMS error (%)	Relative Max. error (%)
Hot-leg LOCA	Core Uncovery	Training data	28.7515	149.2150
		Test data	25.8461	56.1748
	CET exceeding 1200˚F	Training data	9.7226	31.1961
		Test data	23.7692	71.5553
	RV failure	Training data	5.3583	24.6294
		Test data	6.1842	14.3349
Cold-leg LOCA	Core Uncovery	Training data	9.6058	32.3800
		Test data	23.6914	71.1662
	CET exceeding 1200˚F	Training data	5.4995	25.2674
		Test data	12.7790	28.4008
	RV failure	Training data	3.8215	9.4534
		Test data	3.8314	7.9845
SGTR	Core Uncovery	Training data	1.4465	4.0497
		Test data	1.5266	3.1270
	CET exceeding 1200˚F	Training data	1.4993	4.6979
		Test data	2.4798	4.4821
	RV failure	Training data	10.7699	31.5813
		Test data	10.0836	18.1581

In this paper, the SVC and GMDH models were trained using the simulation data set (training data) prepared for training and were confirmed using another simulation data set (test data) independent of the training data. A total of 330 accident simulations were carried out using the MAAP4 code to acquire data, and were composed of 110 hot-leg LOCA, 110 cold-leg LOCA and 110 SGTR. Among a total of 100 simulation data for each scenario divided into two data case: 99 training data and 11 test data. The SVC models identify the LOCA locations accurately. Moreover, it was verified how well the proposed GMDH models estimate time for core uncovery, core exit temperature (CET) exceeding $1200^o F$ and reactor vessel failure. Table 1 and Fig. 1 show the performance of the proposed GMDH.

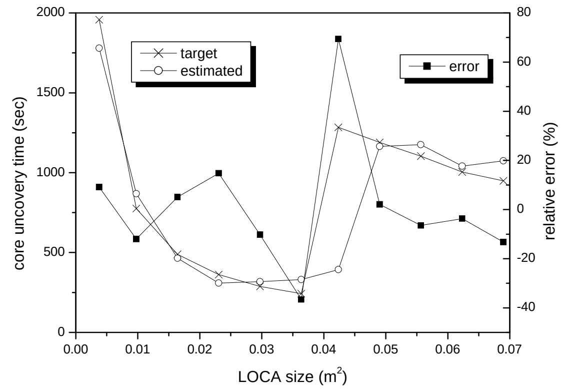

Fig. 1. Reactor core uncover time due to hot-leg LOCA

4. Conclusions

In this study, loss of coolant accidents (LOCA) was diagnosed using SVC and GMDH models. The SVC models were used as a non-linear pattern classifier. The SVC and GMDH models were trained using the training data prepared for training and were confirmed using test data different from the training data. These data sets are prepared from lots of numerical simulations using MAAP4 code since there are no real accident data. The 300 training data were used to develop the SVC and GMDH models, and the 30 test data were used to independently verify whether or not the SVC and GMDH models work well. The performance of the proposed GMDH algorithm can accurately predict the break size.

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