[UCI]I804:24011-200000256855

2012년 2월
석사학위논문

Prediction of Major Transient Scenarios for Severe Accidents of NPPs Using Artificial Intelligence Methods

조 선 대 학 교 대 학 원

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-인공지능 방법을 이용한
원전 중대사고의 과도 시나리오 예측-

2012년 2월 24일

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이 논문을 공학 석사학위신청 논문으로 제출함

2011년 10월

조 선 대 학 교 대 학 원

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2011년　11월

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CONTENTS

List of Tables

List of Figures

초 록

인공지능 방법을 이용한
원전 중대사고의 과도 시나리오 예측

노 영 규
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일본의 후쿠시마 원자력발전소 사고 이후에, 원자력발전소의 중대사고에 대한 우려가 높아지고 있다. 한편, 주요 중대사고 시나리오는 운전원 및 기술요원들이 예측하고 파악하기가 매우 어렵다. 따라서 중대사고를 효율적으로 관리하기 위해서는 원전 중대사고를 위한 주요 과도 시나리오 및 사고 상황을 정확히 예측하고 식별함으로써 운전원과 기술요원들에게 중요하고 가치 있는 정보를 제공해야 한다. 이에 따라, 본 논문에서는 인공지능 방법론 중에서 Support Vector Classification(SVC) 모델 및 Group Method of Data Handling(GMDH) 모델을 적용하여 중대사고의 주요 과도 시나리오에 대한 예측기법을 개발 및 검증하였다. SVC 모델은 고온관 Loss of Coolant Accident(LOCA), 저온관 LOCA, Steam Generator Tube Rapture(SGTR)와 같은 초기사건을 분류하기 위해 개발되었고, GMDH 모델은 중대사고의 주요 과도 시나리오를 나타내는 주요한 시점(원자로노심의 노출 시점, 노심출구온도가 1200°F를 초과하는 시점, 원자로용기의 파손 시점 등)을 정확하게 예측하기 위해 개발되었다.

고온관 LOCA 및 저온관 LOCA, 그리고 SGTR의 각 사고 유형에 대해 각각 110개씩 총 330개의 MAAP4 코드 사고 시뮬레이션 데이터를 이용하였다. SVC와 GMDH 모델의 입력 변수들은 15개의 모의센서의 시간에 따른 적분된 신호가 이용되었으며,

입력 신호는 측정된 신호의 적분값과 시나리오 시점 사이에 상관관계 정도를 고려하여 선택되었다. 또한, GMDH 모델을 위한 입력 변수는 고온관 LOCA, 저온관 LOCA, SGTR에 대하여 원자로 정지 후 30~90초 이내에 아주 짧은 측정신호의 적분한 값이 이용되었다. 선택된 입력 변수와 최대 예측 오차 및 RMS 오차, 측정 오차의 존재에 따른 GMDH 모델의 성능을 분석한 결과, SVC 모델은 모든 경우에 대하여 초기 사건을 정확히 진단하였으며, GMDH 모델은 정확히 중대사고 시나리오를 나타내는 주요한 시점을 예측할 수 있었다. 또한, 이전에 연구되어진 Fuzzy Neural Network(FNN)과 GMDH 모델의 성능 비교 결과, GMDH 모델이 FNN 모델보다 예측 성능의 우수성이 확인되었다. 따라서 SVC와 GMDH 모델과 같은 인공지능 기법이 실제 원자력발전소의 중대사고 시나리오를 식별하고 예측하는데 적용가능성이 기대된다.

I . Introduction

When transient or accidents occur in nuclear power plants, the plant operators are generally provided with only partial information. Even if the operators obtain sufficient information to cope with that condition, they are not allowed sufficient time to analyze the accident in urgent situations.

In the initial stages of an accident, plant operators will attempt to analyze the abnormal plant states by observing the temporal trends of a few important parameters. On the other hand, it is very difficult for operators to predict the progression of an accident by just observing these temporal trends on large display panels in the main control room. In addition, the operators will be faced with hundreds of instrument readings and alarms that will show some typical patterns of that accident. Therefore, the condition may increase the level of confusion with reactor operators.

Accident management has grown in importance as a method for preventing the confusion from that condition and can be accomplished successfully from the operator's high level knowledge as to what the initiating events are and where they have occurred. This knowledge can be collected and learned from important information obtained from a range of measured data. Therefore, it is expected that artificial intelligence (AI) techniques equipped with learning systems can be applied to accident management. In addition, many scientists have already been studying accident management including event identification using AI techniques [1]-[5]. AI techniques were recently applied to the instrument and system monitoring of nuclear engineering fields [6]-[7].

To manage severe accidents at nuclear power plants effectively, it is important to predict and identify the accident initiating events within an initial short time interval after the accidents by observing the major measured signals. Therefore, an accurate prediction of the initiating events, such as the loss of coolant accident (LOCA), total loss of feed water (TLOFW), station blackout (SBO), steam generator tube rapture (SGTR) and major plant scenarios for severe accidents is needed to manage severe accidents.

The objective of this thesis is to develop and verify the prediction techniques for severe accidents using AI methods such as support vector classification (SVC) [4] and group method of data handling (GMDH) [8]-[10] models. The inputs to the SVC and GMDH models are the time-integrated values of the important measured signals during a short time interval after a reactor scram. The SVC and GMDH models were used for event classification among the initiating events and to predict severe accidents, respectively. The data applied for prediction were acquired by carrying out simulations through MAAP4 code [11] for the advanced power reactor 1400(APR1400), which is an advanced pressurized water reactor developed by the Korea Hydro & Nuclear Power company(KHNP).

Ⅱ. Prediction of Transient Scenarios for Severe Accidents

A. Initiating Event Classification Using SVC Model

An SVC model can construct a decision rule to classify the initiating events into one of two classes based on a training data set. Several combined SVC models can solve a general multi-class classification problem that can be extended easily from binary classification. Therefore, the binary classification will be described in this section. The binary classification problems are given N training data $T=\{(\boldsymbol{x}_i, y_i)\}_{i=1}^{N}$, where $x_i \in R^m$ is the input data vector and y_i indicates two classes of $y_i \in \{+1, -1\}$. In the case that two classes can be divided linearly, the event classification is accomplished by defining a hyperplane $(w \cdot x + b = 0)$ that divides the training data set, where the coefficient vector w and bias b determine the hyperplane.

According to the binary classification in Fig.1, the distance between the two parallel lines of $w \cdot x + b = 1$ and $w \cdot x + b = -1$ is $2/\|w\|$. The separating hyperplane will be optimal if the distance between the two parallel lines is a maximum for a given dataset. Therefore, $w^T w$ should be minimized to maximize the distance between the two parallel lines. The generalized optimal separating hyperplane is determined by minimizing the following functional as follows:

$$\Phi(w, \xi) = \frac{1}{2} w^T w + \lambda \sum_{i=1}^{N} \xi_i \tag{1}$$

subject to the constraints

$$\begin{cases} y_i(w \cdot x_i + b) \geq 1 - \xi_i, & i = 1, 2, \cdots, N \\ \xi_i \geq 0, & i = 1, 2, \cdots, N \end{cases} \tag{2}$$

where

$w = [w_1 \ \ w_2 \ \ \cdots \ \ w_N]^T$

$\xi = [\xi_1 \ \ \xi_2 \ \ \cdots \ \ \xi_N]^T$

Even in the case that a hyperplane can correctly separate the data, to consider the noise on the data, a method for introducing an additional non-negative parameter ξ_i in the second term of Eq. (1) was used to deal with the problems associated with a misclassification due to noise. The parameter ξ_i is a measure of the misclassification errors. Fig. 1 gives an example of a misclassification due to noise in the measured data [12]. The filled triangle and circle indicate the data with the measurement noise. The parameter, λ called a regularization parameter controls the trade-off between the complex degree of the SVC model and the classification error.

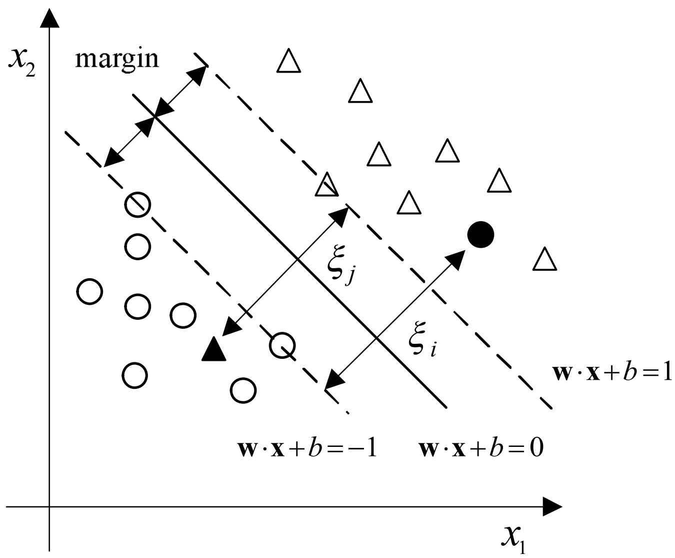


Fig. 1. Example of a binary classification and a misclassification due to noise in the measured data [5][12].

In the case where the linear boundary in the input spaces cannot separate the two classes properly, it is possible to create a hyperplane that allows linear separation in higher dimensional feature space. The SVC models resolve this problem by implicitly mapping the training data into higher dimensional feature space. That is, the primal space is transformed into high dimensional feature space by a nonlinear map $\phi(x)$, as shown in Fig. 2. The function $\phi(x)$, is called the feature that is mapped non-linearly from the input space x, where $\phi = [\phi_1 \ \ \phi_2 \ \ \cdots \ \ \phi_N]^T$.

Fig. 2 shows the hyperplane established in high dimensional feature space and the nonlinear classification problem is converted into a linear classification in high dimensional feature space. The Lagrange multiplier technique and standard quadratic optimization technique can be used to solve the vector w and bias b, and the solution to the convex optimization problem can be expressed as follows:

$$f(x) = sgn\left(\sum_{i \in SVs} \alpha_i y_i K(x_i, x) + b\right) \tag{3}$$

where $b^* = -\frac{1}{2}\sum_{i=1}^{N}\alpha_i y_i [K(x_i, x_r) + K(x_i, x_s)]$ is a bias term and $K(x_i, x) = \phi^T(x_i)\phi(x)$ is called the kernel function. In this thesis a radial basis function $K(x_i, x) = \exp\left(-\frac{(x-x_i)^T(x-x_i)}{2\sigma^2}\right)$ was used because the radial basis function showed the best performance in a number of simulation applications.

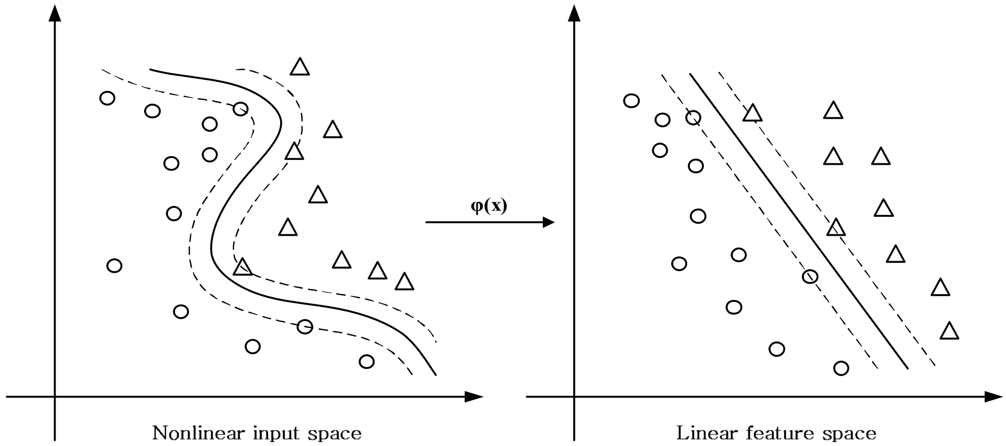


Fig. 2. Mapping to linear feature space from nonlinear input space [5].

In this thesis, SVC models are used as a non-linear pattern classifier that classifies the initiating event representing the hot-leg LOCA, cold-leg LOCA and SGTR using a very short time integration of some selected signals immediately after a reactor scram. The input variables to the SVC models consist of the signals acquired from the reactor coolant system, steam generators and containment at a nuclear power plant. These signals provide information on the initiating event, such as hot-leg LOCA, cold-leg LOCA and SGTR.

B. Accident Scenario Prediction Using GMDH Model

If plant operators follow accident management guidelines strictly or safety systems work properly, a severe accident is unlikely to proceed forward from an initiating event. On the other hand, it is very difficult for operators to follow the guidance and for systems to work well all the time during a plant's lifetime. Therefore, studies of situations leading to a severe accident are needed.

In this thesis, the GMDH model was designed to predict the timings when the reactor core will be exposed, when core exit temperature (CET) will exceed 1200°F, where severe accident management is normally initiated, and when a reactor vessel will fail. The proposed accident scenario prediction algorithm is intended to provide plant operators with valuable information, such as the core exposure time and reactor vessel failure time, so that they can perform severe accident management successfully.

The GMDH model was invented by A.G. Ivakhnenko [8] from the Institute of Cybernetics, Ukrainian Academy of Sciences, but enhanced by others. This model is also known as 'polynomial networks'. Ivakhenenko developed GMDH for the purpose of building more accurate predictive models of fish populations in rivers and oceans. The GMDH worked well for modeling fisheries and many other modeling applications [8].

Generally, the GMDH model is to find the function that most represented given independent variables as the dependent variables. It considers the independent variables as individual objects of current generation. This method selects the two random independent variables among the object, then create an expression that represents the dependent variables by the value of that independent variables, and then, that recognize as an object of new generation. The value of an object that obtained the value of independent variables by putting on a created object is recognized as a new data point. And then, it is repeated for each possible combination of independent variables. This process is similar to that make generational change, it create a new expression that represent the dependent variable after select random two objects among the created objects. It finds the best object from the descendant generation over repeat the generation replacement process.

The GMDH algorithm uses the data structure similar to multiple regression models to improve the accuracy of prediction and to select optimum structure of model. Acquired data is usually divided into three subsets (training data set, verification data set, test data set). Because, this is to maintain the model normalization and to avoid the over-fitting by the cross-validate. The Fig. 3 shows the data structure used in the GMDH model.

$$
\begin{array}{ll}
\text{training data set} & \left\{\begin{array}{ccccc} x_{11} & x_{12} & \cdots & x_{1m} & y_1 \\ x_{21} & x_{22} & \cdots & x_{2m} & y_2 \\ \cdot & \cdot & \cdot & \cdot & \cdot \\ \cdot & \cdot & \cdot & \cdot & \cdot \\ \cdot & \cdot & \cdot & \cdot & \cdot \\ x_{l1} & x_{l2} & \cdots & x_{lm} & y_l \end{array}\right. \\
\text{verification data set} & \left\{\begin{array}{ccccc} \cdot & \cdot & \cdot & \cdot & \cdot \\ \cdot & \cdot & \cdot & \cdot & \cdot \\ \cdot & \cdot & \cdot & \cdot & \cdot \\ x_{n1} & x_{n2} & \cdots & x_{nm} & y_n \end{array}\right. \qquad \rightarrow \text{development data} \\
 & \begin{array}{ccccc} \cdot & \cdot & \cdot & \cdot & \cdot \\ \cdot & \cdot & \cdot & \cdot & \cdot \\ \cdot & \cdot & \cdot & \cdot & \cdot \\ x_{K1} & x_{K2} & \cdots & x_{Km} & y_K \end{array} \\
\text{test data set} & \left\{\begin{array}{ccccc} \cdot & \cdot & \cdot & \cdot & \cdot \\ \cdot & \cdot & \cdot & \cdot & \cdot \\ \cdot & \cdot & \cdot & \cdot & \cdot \\ x_{N1} & x_{N2} & \cdots & x_{Nm} & y_N \end{array}\right.
\end{array}
$$

Fig. 3. GMDH data structure [5]

The GMDH uses a self-organizing modeling algorithm that can flexibly choose nonlinear forms of the basic inputs $\{x_1, x_2, \cdots, x_m\}$. Fig. 4 shows the branch structure of the GMDH algorithm. It starts with the basic inputs at the first level and becomes more complex according to the increasing number of layers [13].

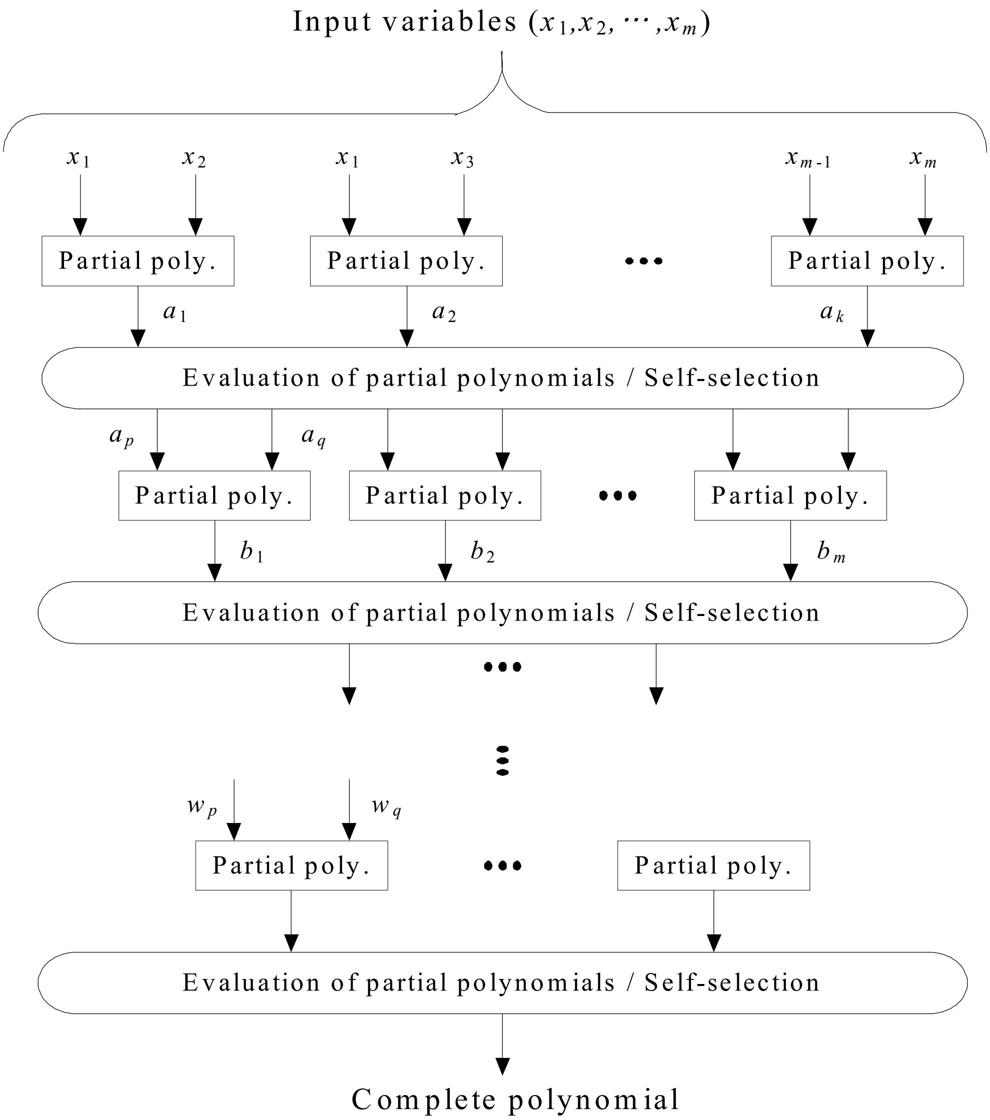


Fig. 4. Branch structure of the GMDH model [14].

The existing GMDH method use a common format as follow at each step about continuous approximation [13-15].

$$y = f(x_i, x_j) = A + Bx_i + Cx_j + Dx_i^2 + Ex_j^2 + Fx_i x_j \tag{4}$$

The coefficient parameters of the reference function written above, such as $A, B, \cdots F$ can be solved using a least squares method in an arbitrary pair (x_i, x_j) out of the independent variables $x = (x_1, x_2, \cdots, x_m)$.

The GMDH algorithm uses the high-order polynomials in the kolmogorov-gabor form [13-16]. The kolmogorov-gabor form called ivakhnenko polynomial can be expressed as follows:

$$y = a_0 + \sum_{i=1}^{m} a_i x_i + \sum_{i=1}^{m} \sum_{j=1}^{m} a_{ij} x_i x_j + \sum_{i=1}^{m} \sum_{j=1}^{m} \sum_{k=1}^{m} a_{ijk} x_i x_j x_k \cdots \tag{5}$$

where $x = (x_1, x_2, \cdots, x_m)$ is an input variable vector and $a = (a_0, a_i, a_{ij}, a_{ijk}, \cdots)$ is a vector of coefficients or a weight of the Kolmogorov-Gabor polynomial.

The GMDH algorithm can determine the structure of a model and modeling the system output about most important input. So, ingredients about aforementioned lower-order polynomials are used. It means that the GMDH algorithm integrate the lower-order polynomials in each generation to reach the next generation. This process is continued until the GMDH model indicate the over-fitting, or until exceed a fixed maximum computation time.

At this point, predicted value $\hat{y}$ is obtained by applying solved basic regression equation to the verification data y, and then the following criteria evaluation value R is obtained after compares checking data. If R is small, it means that prediction ability is excellent, if R is large, it means that prediction ability is not good.

$$R^2 = \sum_{s \in N} (y_s - \hat{y_s})^2 / \sum_{s \in N} y_s^2, \quad R = \sqrt{R^2} \tag{6}$$

If the value of obtained criteria evaluation R is larger than pre-set standard value, regression equation by the current pairs is culled. And if smaller than critical value, it can be survived. $\hat{y}$ value obtained by applying survived regression equation to the data of training set keep to the value of next generation, and then shall be the new training data set. This process is conducted for every pair of independent variables as possible. Among the generated descendants, descendant of the least evaluation value R is remembered as the optimum fit of the generation, then the criteria evaluation value is remembered as $R_g^{\min}$. Through this generation change, $R_g^{\min}$ for each generation decreases gradually and then is increased again. Fig. 5 shows that evolutionary process of the generation replacement is important.

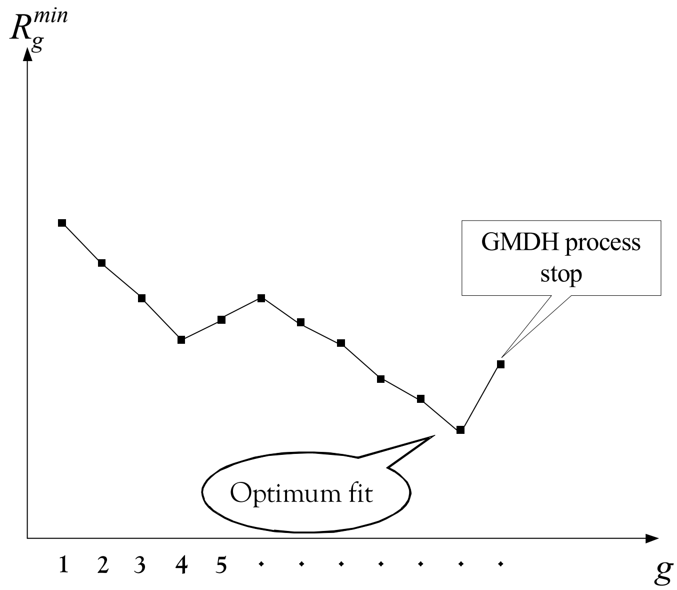


Fig. 5. Trend of the $R^{\min}$ values according to the generations [13].

The GMDH algorithm generates and tests all the input-output combinations in a system. Each element of the system performs the function of two inputs. The elements mean the blocks in Fig. 4. The coefficient parameters were decided using a normal least squares method and then, the variables of the elements were calculated. The threshold value at each generation determines if the outputs of the elements in a generation are acceptable. In this thesis, the threshold at each generation was redefined as the minimum fractional error of Eq. (7) at the very previous generation. The output of an element was eliminated in a current generation when the result is larger than the threshold value. Those variables or elements, which are useful for predicting the proper output, were used at the next generation. The generations were repeated until satisfactory results could be obtained. This process is similar to Darwin's theory. The detailed main implementation steps are given below [13]:

First, construct each pair of input and output variables or data of the object system to be modeled and divide the training and verification data sets. Preprocess the data to normalize the data sets. Second, choose the external inputs to the GMDH network. Calculate the regression polynomial parameters for each pair of input variables (x_i, x_j) and its associated output y in the training data set. Calculate the regression parameters using the least squares method. Compute the $m(m-1)/2$ high-order variables in place of the original input variables $x_1, x_2, \cdots, x_m$ to predict the output y. Apply ridge regression to avoid the collinearity problem. Third, construct a group of new variables $z_{g1}, z_{g2}, \cdots, z_{gm_g}$ $((m_g = m_{g-1}(m_{g-1}-1)/2))$ in the former step, where m_g is the number of input variables for generation g. Some of these variables will take the place of the old predictors in the next generation. Estimate each new variable by deciding which variable best evaluates the dependent variable, y. The criterion used to evaluate the new variables at generation g is the fractional error for the verification data, which is defined as follows:

$$r_j^2 = \frac{\sum_{i=l+1}^{n} (y_i - z_{ij})^2}{\sum_{i=l+1}^{n} y_i^2} \quad \text{for } j = 1, 2, \cdots, m_g. \tag{7}$$

Arrange the columns of the new variable z_g according to the magnitude of r_j. An arbitrary cut-off value R needs to be selected by the analyst. All the columns of z_g satisfying $r_j < R$ are chosen to replace the input terms in the previous generation, and all the variables with $r_j < R$ are screened out and not passed into the next generation of the algorithm (refer to Fig. 5). At last, when over-fitting is observed through cross checking, the process mentioned above is stopped, the minimum r_j value for generation g is denoted as $R_g^{\min}$. The training and checking processes stops if $R_g^{\min} > R_{g-1}^{\min}$. When the above condition is satisfied, the model will begin to become over-fitted if the generation continues. The polynomial with the minimum error criterion in generation $g-1$ is selected at the final approximate model. Otherwise, the algorithm moves to the next generation and the above steps are repeated (refer to Fig. 5).

$R_g^{\min}$ which is picked as the best of the quadratic polynomials in each generation, has a quadratic shape [13], as shown in Fig. 5, showing that the GMDH converges to a minimum value. As the generation proceeds from the bottom to the top in Fig. 4, the branch structure of the GMDH model becomes more complex and the empirical error of the GMDH model for a training data decreases continuously. Compared to the training data, the empirical error of the GMDH model for a verification data tends to decrease at an early stage with increasing number of generations but the error for the verification data increases as the GMDH model becomes more and more complex. The small error for the training data and the large error for the verification data indicate that the GMDH model is overfitted. Fig. 5 shows the fractional error of the verification data set.

All quadratic regression parameters are stored at the end of the GMDH algorithm procedure, and the estimated coefficients for the high order polynomial are determined by back tracing the GMDH architecture until the original variables are reached. In addition, the change in the generations that generate the optimum fit can be expressed as a type of tree called the Ivakhnenko tree (see Fig. 6) [16].

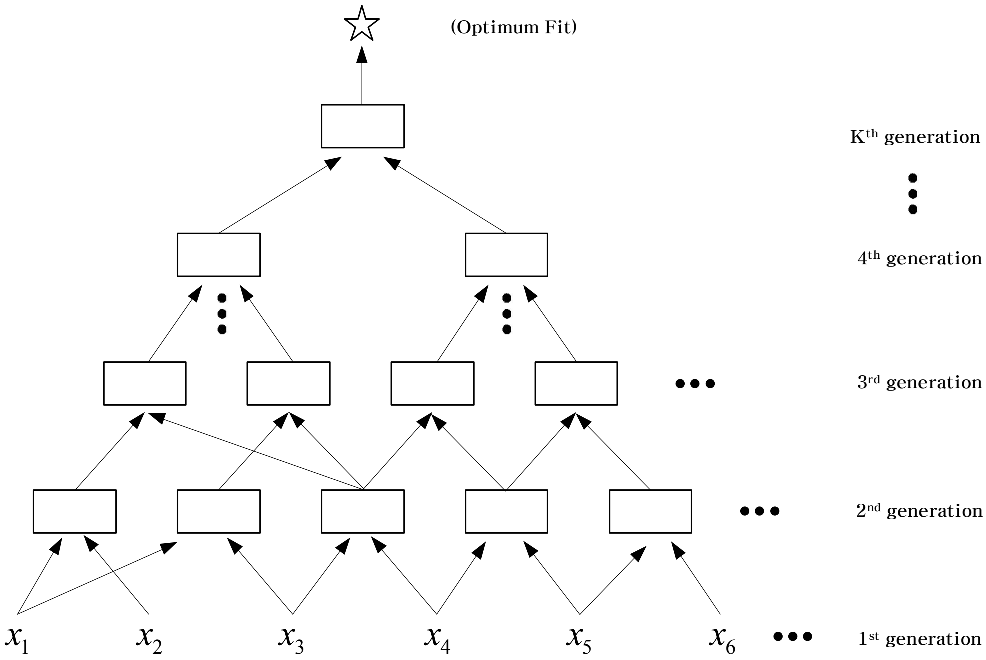


Fig. 6. Ivakhnenko tree

Equation $y=f(x_i,x_j)=A+Bx_i+Cx_j+Dx_i^2+Ex_j^2+Fx_ix_j$ for a given data set is generally expressed as $XW=Y$ where the coefficient vector W includes $A,B,\cdots F$. There are several problems in solving the coefficient vector W. Among them, collinearity is a problem commonly encountered during complex system modeling. In this thesis, ridge regression was used to solve the collinearity problem. The coefficient vector W was calculated from the ridge regression of the following form instead of $W=(X^TX)^{-1}X^TY$ because the calculation of X^TX might induce a numerical problem:

$$W=(X^TX+\alpha I)^{-1}X^TY \tag{8}$$

where (X^TX) is the correlation matrix for the predictors, (X^TY) is the vector of the correlations between the predictors and the dependent variable, $\alpha \geq 0$ is a scalar constant and I is the identity matrix.

C. Selection of the Training Data

A GMDH model can be well trained using informative data. The input and output training data exist in the form of clusters and the data at these cluster centers is more informative than the neighboring data. Fig. 7 shows the data clusters and their centers for simple two-dimensional data. In this thesis, the cluster centers were determined using a subtractive clustering (SC) scheme [17] and were used as the training data set.

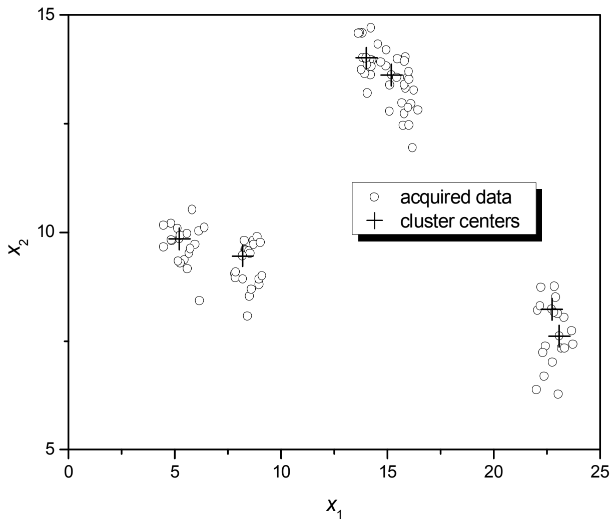


Fig. 7. Data clusters and cluster centers for simple two-dimensional data

The information potential of each data point is defined as a function of the Euclidean distances to all other input data points [17].

$$P_1(i) = \sum_{j=1}^{N} e^{-4\|\boldsymbol{x}_i - \boldsymbol{x}_j\|^2 / r_\alpha^2},\ i = 1,2,\cdots,N \tag{9}$$

where a positive constant r_α is a radius defining a particular neighborhood of the cluster. The potential of a data point to be cluster center is higher when it is surrounded by an amount of neighboring data. After calculating the potential of each data point, the data point with the highest potential is considered as first cluster center. Each time a cluster center is obtained. In general, after determining the k-th cluster center $\boldsymbol{c}_k$ and its potential value P_k^c, the potential of each data point is recalculated using the following equation:

$$P_{k+1}(i) = P_k(i) - P_k^c e^{-4\|\boldsymbol{x}_i - \boldsymbol{x}_k^c\|^2 / r_\beta^2},\ i = 1,2,\cdots,N \tag{10}$$

where a positive constant r_β denotes radius of the neighborhood. Also, r_β is usually greater than r_α in order to limit the number of clusters generated. When the potentials of all data points are recalculated using Eq. (10), the data point with the highest potential is selected as the $(k+1)^{\text{th}}$ cluster center. The calculation stops if $P_k^c < \zeta P_1^c$ is true, otherwise calculation continues. If the calculation stops at an iterative step N_c, this means there are N_c cluster centers. Through this procedure, the input/output data positioned in the cluster centers were selected to train the GMDH model.

Ⅲ. Verification of the Proposed Algorithm

To verify the proposed algorithm, it was necessary to acquire the data needed to train the AI techniques from a number of numerical simulations owing to few real LOCA. A total of 330 accident simulations data were carried out using the MAAP4 code to acquire data. The following 15 simulated sensor signals acquired from these simulations were used; core exit temperature, containment pressure and temperature, pressurizer pressure and water level, sump water level, collapsed water level, etc. The containment pressure and temperature are the values measured at the central position of a containment that is located between the operating deck and the polar crane, which is known as an upper compartment below the dome. APR1400 has two steam generators. The terms 'broken side S/G' and 'unbroken side S/G' corresponds to the two steam generators that are connected to a broken hot-leg (or cold-leg, SGTs) and an unbroken hot-leg (or cold-leg, SGTs), respectively. The input variables to the SVC and GMDH models are the time-integrated values of 15 simulated sensor signals as follows:

$$x_j = \int_{t_s}^{t_s + \triangle t} g_j(t)dt,\ j = 1, 2, \cdots, 15 \tag{11}$$

where $g_j(t)$ is a specific measured signal, t_s is the scram time and $\triangle t$ is the integrating time span.

A total of 330 accident simulations were classified into 3 types of initiating events, such as hot-leg LOCA, cold-leg LOCA and SGTR. To confirm the event classification by the proposed algorithm, a total of 330 simulation data were divided into both model development data and test data. The model development data was used to develop the proposed algorithm and the test data was used to test it independently. Therefore, a total of 300 simulation data was utilized to develop the proposed SVC classification algorithm, and consisted of 100 hot-leg LOCAs, 100 cold-leg LOCAs and 100 SGTRs. And the remaining 30 test simulation data consisted of 10 hot-leg LOCAs, 10 cold-leg LOCAs and 10 SGTRs.

In this thesis, the integrating time span in Eq. (11) for the SVC model was 60 sec, which means that the SVC model use the time-integrated signals of 60 sec time intervals immediately after a reactor scram. The integrating time span was selected using several numerical simulations of the proposed algorithm to minimize the classification error. The two SVC models were trained so that they categorize the hot-leg LOCA, cold-leg LOCA, and SGTR as (1, 1), (1, -1), and (-1, -1), respectively, as shown in Table 1. The SVC can classify the initiating events accurately for training and test data.

TABLE 1. Initiating event classification of the training and test data using SVC.

	Break size (cm^2)	Hot-leg LOCA			Cold-leg LOCA			SGTR		
		Scram time (sec)	Classified		Scram time (sec)	Classified		Scram time (sec)	Classified	
			SVC1	SVC2		SVC1	SVC2		SVC1	SVC2
100 Training simulations	4.50	909.91	1	1	568.91	1	−1	45.53	−1	−1
	11.15	761.91	1	1	224.91	1	−1	45.76	−1	−1
	17.80	646.91	1	1	137.91	1	−1	45.54	−1	−1
	~(94)	~(94)	1	1	~(94)	1	−1	~(94)	−1	−1
	716.35	7.42	1	1	5.98	1	−1	7.60	−1	−1
	723.01	7.38	1	1	5.95	1	−1	7.55	−1	−1
	729.66	7.34	1	1	5.92	1	−1	7.50	−1	−1
10 Test simulations	37.76	126.91	1	1	64.41	1	−1	9.81	−1	−1
	104.29	38.99	1	1	23.78	1	−1	8.73	−1	−1
	~(6)	~(6)	1	1	~(6)	1	−1	~(6)	−1	−1
	616.56	8.22	1	1	6.46	1	−1	8.22	−1	−1
	689.74	7.62	1	1	6.12	1	−1	7.62	−1	−1

This thesis examined how well the proposed accident scenario prediction algorithm using the GMDH model predicts the timings when the reactor core will be uncovered, when the CET will exceed 1200°F, and when the reactor vessel will fail.

The integrating time span in Eq. (11) depends on the types of input signals and initiating events. The time span was determined by the correlation degree between the related timing and integrated input signals (refer to Table 2). This means that the GMDH model can predict these important scenario timings by using the initial short time integration of the measured input signals for 30 sec to 90 sec immediately after the reactor scram. In addition, the optimal input selection process was performed using a genetic algorithm. Table 2 lists the selected inputs and integrated time spans according to the input signals and the initiating events. Moreover, a total of 100 model development data were divided into two data sets; training data (80 data points) and verification data (20 data points). The training data was used to train the GMDH model and the verification data was used to prevent over-fitting.

TABLE 2. Selected input variables and integrating time span

(a) Hot-leg LOCA

Scenario type	Selected inputs	Integrating time span (sec)
Core exposure time	Pressurizer water level	90
	Collapsed sump water level	30
	Collapsed water level	40
	Unbroken side S/G water temperature	60
Time that CET exceeds 1200°F	Containment pressurizer	30
	Containment gas temperature	90
	Pressurizer water level	50
	Collapsed water level	90
Reactor vessel failure time	Pressurizer pressure	30
	Pressurizer water level	30
	Broken side S/G water level	90

TABLE 2. Contiuned

(b) Cold-leg LOCA

Scenario type	Selected inputs	Integrating time span (sec)
Core exposure time	Collapsed sump water level	30
	Collapsed water level	60
	Broken side S/G water level	30
	Broken side S/G pressure	60
	Unbroken side S/G water level	30
	Unbroken side S/G pressure	70
Time that CET exceeds 1200°F	Containment gas temperature	40
	Pressurizer pressure	90
	Unbroken side S/G water level	90
	Broken side S/G water temperature	30
Reactor vessel failure time	Containment Pressurizer	90
	Pressurizer pressure	30
	Broken side S/G water level	90

(c) SGTR

Scenario type	Selected inputs	Integrating time span (sec)
Core exposure time	Collapsed water level	90
	Broken side S/G water level	30
	Unbroken side S/G water level	90
Time that CET exceeds 1200°F	Core exit temperature	30
	Pressurizer pressure	30
	Broken side S/G water level	30
Reactor vessel failure time	Core exit temperature	30
	Pressurizer water level	30
	Broken side S/G water temperature	30

Table 3 lists the prediction errors for hot-leg LOCA of the GMDH model. A comparison of the results of the training data and test data revealed a large difference between the relative error and RMS error because the test data size is too small. On the other hand, these differences can be decreased by providing sufficient simulation data. Tables 4 and 5 list the prediction errors for cold-leg LOCA and SGTR, respectively.

Table 3. Prediction errors for hot-leg LOCA

Scenario type	Training data		Test data	
	RMS error(%)	Relative Max. error(%)	RMS error(%)	Relative Max. error(%)
Core exposure time	16.6385	54.0076	14.1283	20.1601
Time that CET exceeds 1200°F	11.9113	64.0588	7.0560	15.6363
Reactor vessel failure time	3.5284	13.3551	12.9123	38.5437

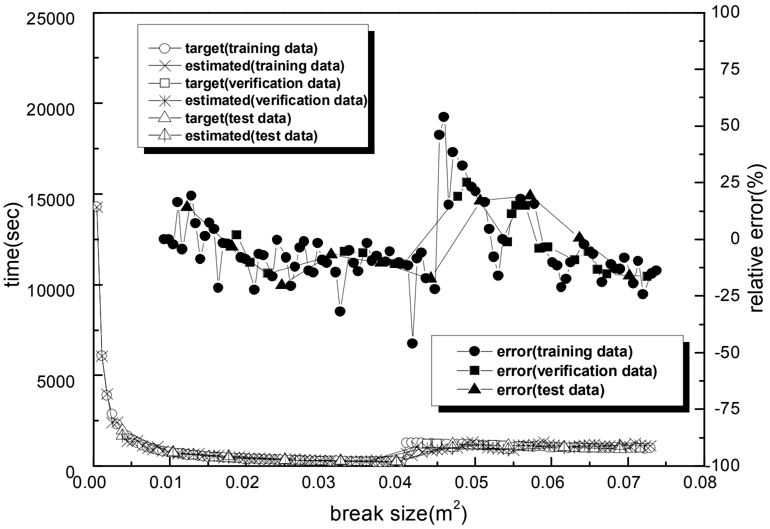
Table 4. Prediction errors for cold-leg LOCA

Scenario type	Training data		Test data	
	RMS error(%)	Relative Max. error(%)	RMS error(%)	Relative Max. error(%)
Core exposure time	11.7598	33.1136	28.8688	73.4936
Time that CET exceeds 1200°F	6.4431	37.5857	18.3856	42.7712
Reactor vessel failure time	3.3921	10.9808	10.1714	30.9587

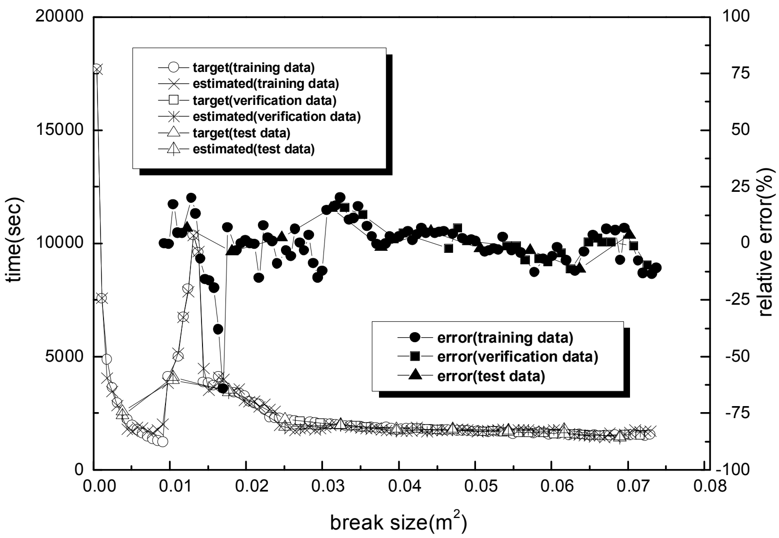
Table 5. Prediction errors for SGTR

Scenario type	Training data		Test data	
	RMS error(%)	Relative Max. error(%)	RMS error(%)	Relative Max. error(%)
Core exposure time	1.4383	4.3843	1.4742	3.5844
Time that CET exceeds 1200°F	1.5897	7.0196	2.0519	5.8674
Reactor vessel failure time	10.9552	27.6353	11.8209	19.4668

Fig. 8 shows important timings in severe accident scenarios that are induced by an initiating event of hot-leg LOCAs. These graphs were intended to show that the proposed algorithm accurately predicts the important timings representing major severe accident scenarios including the predicted timings and their errors. The timing values are indicated in the left vertical axis and the relative prediction errors are indicated in the right vertical axis. Fig. 8(a) shows the target and predicted timings for reactor core exposure using four input variables (refer to Table 2(a)). In this figure, the relative error represents the percent error of $\left(y_k - \widehat{y_k}\right) / y_k$. The large relative error at a test data are caused by the relatively small target value. The predicted value was similar to the target value. In addition, it will be possible to reduce the error by training the GMDH model with more training data. Fig. 8(b) shows the target and predicted timings for the time that CET exceeds 1200°F using four input variables (refer to Table 2(a)). Fig. 8(c) shows the target and predicted timings for the reactor vessel failure time using three input variables (refer to Table 2(a)). Fig. 8 shows that the proposed GMDH model can predict accurately the important timings for severe accident scenarios that are initiated by a hot-leg LOCA. The graphs related to the cold-leg LOCA were omitted because they were similar to the hot-leg LOCA case.

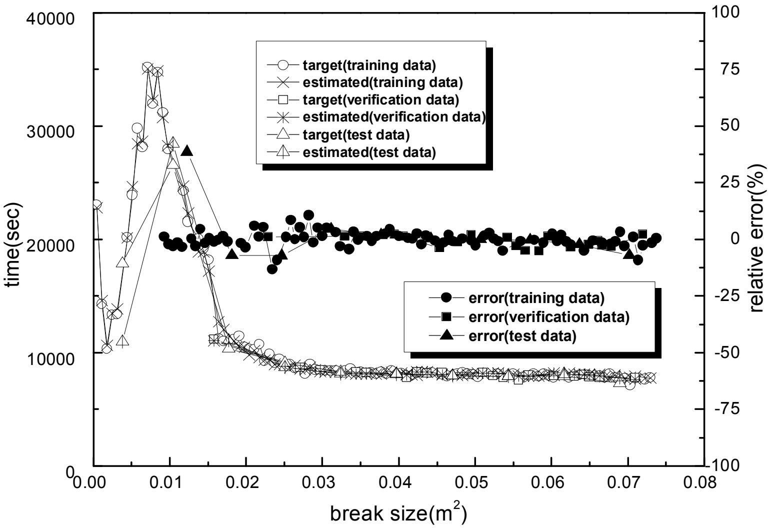


(a) Reactor core exposure time



(b) Time that CET exceeds

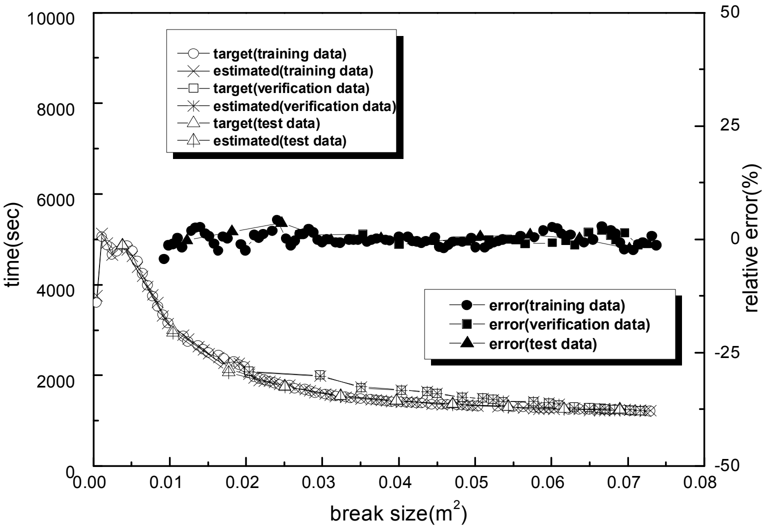
Fig. 8. Important scenario timings due to the initiating event of hot-leg LOCAs



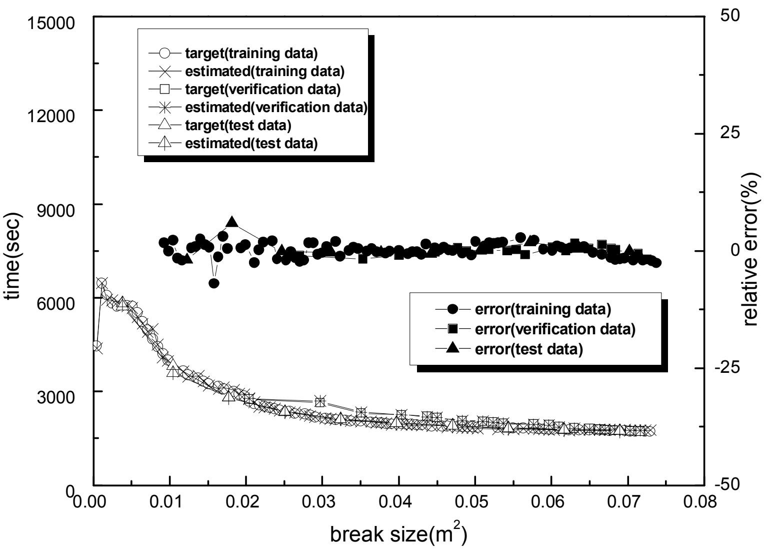
(c) Reactor vessel failure time

Fig. 8. Contiuned

Fig. 9 shows important timings in severe accident scenarios that are induced by an initiating event of SGTR. Fig. 9(a) shows the target and predicted timings for the reactor core exposure by three input variables (refer to Table 2(c)). Fig. 9(b) shows the target and predicted timings for the time that the CET exceeds using three input variables (refer to Table (c)). Fig. 9(c) presents the target and predicted timings for reactor vessel failure time using three input variables (refer to Table (c)). Fig. 9 shows that the proposed GMDH model can accurately predict some important timings for severe accident scenarios that are initiated by the SGTR.

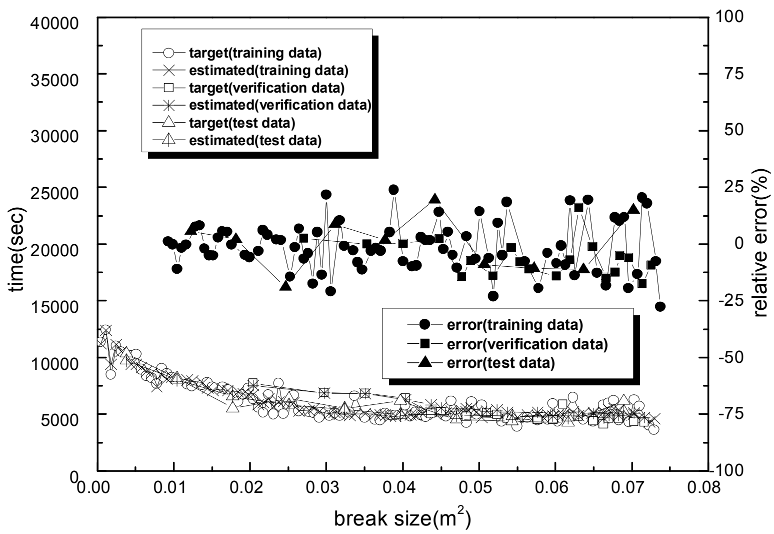


(a) Reactor core exposure time



(b) Time that CET exceeds

Fig. 9. Important scenario timings due to the initiating event of SGTR



(c) Reactor vessel failure time

Fig. 9. Contiuned

Table 6 shows the comparison of the proposed GMDH model with previously studied fuzzy neural network (FNN) [3]. Note that GMDH and FNN models used the same data and conditions. Comparing the performance of developed two models, it is from the Table 6 known that the GMDH model is slightly superior to the FNN model for severe accident scenarios. The reason why the results of the FNN model are different from the previous result [3] is that more simulation data was used in the present study.

Table 6. Comparison of the performance of two developed models (GMDH, FNN)

Initiating Event	Scenario type	GMDH model	FNN model
		RMS error(%)	RMS error(%)
Hot-leg LOCA	Core exposure time	15.7101	16.5496
	Time that CET exceeds 1200°F	10.7640	17.7667
	RV failure time	5.0384	4.7468
Cold-leg LOCA	Core exposure time	13.8685	34.6682
	Time that CET exceeds 1200°F	7.9373	8.6023
	RV failure time	4.3734	7.0943
SGTR	Core exposure time	1.3699	2.1122
	Time that CET exceeds 1200°F	1.5448	1.8323
	RV failure time	10.8637	11.6426

Ⅳ. Conclusions

To manage severe accidents effectively in the nuclear power plants, many studies on accident management including event identification using artificial intelligence(AI) techniques have been proceeding briskly. In this thesis, the suppot vector classification(SVC) model was designed to classify the initiating events into 3 types of categorized events, such as hot-leg loss of coolant accident(LOCA), cold-leg loss of coolant accident(LOCA) and steam generator tube rapture(SGTR). In addition, the group method of data handling(GMDH) model was used to predict severe accidents and developed to predict the important timings representing severe accident scenarios, such as the reactor core exposure time, the time that core exit temperature(CET) exceeds 1200°F and the reactor vessel(RV) failure time due to LOCA. The proposed SVC and GMDH algorithms were applied and verified using the data acquired through the MAAP4 code. In addition, more informative data obtained from an SC scheme were used to train that model.

The simulation results showed that the proposed SVC can accurately classify many initiating events into 3 types of categorized events, such as hot-leg LOCA, cold-leg LOCA and SGTR. And the proposed GMDH model could predict within approximately 20% RMS error the important timings representing severe accident scenarios, such as the reactor core exposure time, the time that CET exceeds 1200°F, and the reactor vessel failure time due to LOCA. In addition, result of the proposed GMDH model was compared with previously studied fuzzy neural network (FNN). As a result the GMDH model is slightly superior to the FNN model. Therefore, it is expected that the SVC and GMDH models can be applied successfully to identify and predict severe accident scenarios in a real NPP.

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감사의 글

나의 대학원 생활의 추억이 담겨있는 NICL..! 처음엔 낯설고 어색한 이곳이 이젠 집보다 더 편한 곳이 되었습니다. 모든 걸 할 수 있다는 자신감과 열심히 하겠다는 마음을 가지고 시작한 대학원 생활에서 벌써 마침표를 찍는 시간이 되었습니다. 2년 동안 '조금 더 열심히 하지 못했을까' 하는 후회로 많은 생각을 갖게 하지만 저를 되돌아 볼 수 있는 시간이 있기에 제가 보다 더 발전할 수 있을 것이라 마음 속 깊이 되새기며 대학원 생활 내내 제게 많은 도움을 주신 분들께 감사의 마음을 전합니다.

먼저 지금의 저를 있게 해주신 영원한 스승님, 나만균 교수님께 머리 숙여 깊은 감사를 드립니다. 한없이 부족한 저에게 수많은 경험과 사회생활을 비롯한 모든 부분에서의 가르침을 마음속에 영원히 간직하겠습니다. 또한, 항상 모든 제자들이 잘 되기만을 바라시며 일일이 챙겨주시는 모습과 변함없는 모습으로 연구에 몰두하시는 열정을 존경합니다. 교수님께 가르침을 받는 2년이란 시간은 저에겐 너무나도 소중하고 행복한 시간이였습니다. 바쁘신 와중에도 시간을 내시어 상담을 하며 많은 조언을 해주신 김숭평 교수님, 정운관 교수님, 이경진 교수님 진심으로 감사드립니다. 제자들과 항상 허물없이 지내고 저에게 칭찬과 격려를 아끼지 않으신 송종순 교수님, 프로젝트를 함께 하면서 많은 가르침을 주신 김진원 교수님 진심으로 감사드립니다. 원자력 분야의 실제적 현장 이야기를 들려주시며 격려를 해주신 신원기 교수님, 이기복 교수님, 이심교 교수님 진심으로 감사드립니다.

처음 NICL에 들어왔을 때 같이 대학원 생활을 하면서 하나라도 더 가르쳐 주려고 하고 많은 관심과 배려를 해준 성한이형 고맙습니다. 나의 고민 상담자 동수, 항상 에너지가 넘치는 심원, 장난도 항상 진지하던 순호, 실험실 막내 같지 않는 막내 주현, 마지막으로 앞으로 들어올 막내들을 데리고 실험실을 책임질 차기 실장 재환, 너희들과 함께한 시간은 나에게 소중한 시간이였다. 정말 고맙다.

각자 실험실에서 대학원 생활을 같이 해오며 도와주신 유선이형, 정민이형, 용진이형, 강일이형, 정현이형에게 고마움을 전합니다. 또한, 학부 생활을 함께한 평규, 상헌,

석철, 민수, 용환 모두 고맙다. 또한, 웅이형, 대섭이형, 영춘이형 정말 고맙습니다. 형의 부탁은 모두 들어 준 후배들 사용, 민영, 태빈, 영국, 현민 모두 고맙다. 이외에도 미처 이름을 언급하지 않은 선, 후배, 동기들에게도 고마움 마음을 전합니다.

항상 친구라는 행복감을 안겨주고 함께 울고 웃으며 10년이 넘는 시간을 함께해준 친구들 우영, 종석, 길호, 길선, 대호, 학주, 정신, 승엽이 등등 너무 고맙고 앞으로 남은 평생 동안 서로 의지하고 잘 지내보자.

마지막으로 저를 지금껏 자신을 희생하시면서 한없이 사랑을 주신 부모님께 머리 숙여 감사의 말씀을 드립니다. 앞으로 자랑스러운 아들이 되도록 노력하겠습니다. 또한, 하나 밖에 없는 동생이라고 항상 챙겨준 누나에게도 감사의 말을 전합니다.

2년이란 시간 나의 아지트였던 NICL을 이제 후배들에게 맡기고 가벼운 마음으로 사회로의 첫발을 내딛으려 합니다. 모두에게 감사함을 전하는 지금, 앞으로 나의 후배들의 아지트가 되어줄 NICL에서...

2011년 12월

NICL에서

노 영 규

저작물 이용 허락서

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논문제목	한글 : 인공지능 방법을 이용한 원전 중대사고의 과도 시나리오 예측				
	영문 : Prediction of Major Transient Scenarios for Severe Accidents of NPPs Using Artificial Intelligence Methods				

본인이 저작한 위의 저작물에 대하여 다음과 같은 조건아래 조선대학교가 저작물을 이용할 수 있도록 허락하고 동의합니다.

- 다 음 -

1. 저작물의 DB구축 및 인터넷을 포함한 정보통신망에의 공개를 위한 저작물의 복제, 기억장치에의 저장, 전송 등을 허락함
2. 위의 목적을 위하여 필요한 범위 내에서의 편집ㆍ형식상의 변경을 허락함. 다만, 저작물의 내용변경은 금지함.
3. 배포ㆍ전송된 저작물의 영리적 목적을 위한 복제, 저장, 전송 등은 금지함.
4. 저작물에 대한 이용기간은 5년으로 하고, 기간종료 3개월 이내에 별도의 의사 표시가 없을 경우에는 저작물의 이용기간을 계속 연장함.
5. 해당 저작물의 저작권을 타인에게 양도하거나 또는 출판을 허락을 하였을 경우에는 1개월 이내에 대학에 이를 통보함.
6. 조선대학교는 저작물의 이용허락 이후 해당 저작물로 인하여 발생하는 타인에 의한 권리 침해에 대하여 일체의 법적 책임을 지지 않음
7. 소속대학의 협정기관에 저작물의 제공 및 인터넷 등 정보통신망을 이용한 저작물의 전송ㆍ출력을 허락함.

동의여부 : 동의(○) 반대( )

2012년 2월 일

저작자: 노 영 규 (서명 또는 인)

조선대학교 총장 귀하