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Prediction of hydrogen concentration in nuclear power plant containment under severe accidents using cascaded fuzzy neural networks

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HIGHLIGHTS

- We present a hydrogen-concentration prediction method in an NPP containment.
- The cascaded fuzzy neural network (CFNN) is used in this prediction model.
- The CFNN model is much better than the existing FNN model.
- This prediction can help prevent severe accidents in NPP due to hydrogen explosion.

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ABSTRACT

Recently, severe accidents in nuclear power plants (NPPs) have attracted worldwide interest since the Fukushima accident. If the hydrogen concentration in an NPP containment is increased above 4% in atmospheric pressure, hydrogen combustion will likely occur. Therefore, the hydrogen concentration must be kept below 4%. This study presents the prediction of hydrogen concentration using cascaded fuzzy neural network (CFNN). The CFNN model repeatedly applies FNN modules that are serially connected. The CFNN model was developed using data on severe accidents in NPPs. The data were obtained by numerically simulating the accident scenarios using the MAAP4 code for optimized power reactor 1000 (OPR1000) because real severe accident data cannot be obtained from actual NPP accidents. The root-mean-square error level predicted by the CFNN model is below approximately 5%. It was confirmed that the CFNN model could accurately predict the hydrogen concentration in the containment. If NPP operators can predict the hydrogen concentration in the containment using the CFNN model, this prediction can assist them in preventing a hydrogen explosion.

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1. Introduction

Ensuring the safety of nuclear power plants (NPPs) has gained much importance around the world since the Fukushima accident. High hydrogen concentration in a containment is directly related to NPP safety. Major hydrogen sources during the development of a severe accident in a LWR are largely classified into: (a) In-vessel metal oxidation (Zr clads and grids and other metallic structures) or B4C absorber material oxidation with steam, (b) Ex-vessel oxidation of metallic material during direct containment heating (DCH), (c) Ex-vessel oxidation of metallic material during molten core concrete interaction (MCCI) (Abou-Rjeily et al., 2011). Consequently, hydrogen is accumulated in the containment. If the hydrogen concentration increases above 4% in atmospheric pressure, hydrogen combustion will likely occur. For example, in the March 2011 Fukushima Daiichi accident – in which the cores of three GE-designed boiling water reactors lost all cooling and melted down – hydrogen leaked from the primary containments into the reactor buildings. The hydrogen accumulated in the reactor buildings and detonated, causing large releases of harmful radionuclides (Leyse, 2014). Thus, the hydrogen concentration must be kept below 4% to maintain containment integrity and prevent explosion. The objective of this study is to predict the hydrogen concentration in the containment under severe NPP accidents.

Diverse artificial-intelligence techniques have been successfully utilized in nuclear engineering area, such as signal validation

Abbreviations: CFNN, cascaded fuzzy neural network; FNN, fuzzy neural network.

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(Hines et al., 1997; Na, 2001; Garvey et al., 2007), plant diagnostics (Bartlett and Uhrig, 1992; Marseguerra and Zio, 1994; No et al., 2012; Gofuku et al., 1988), event identification (Na et al., 2004; Cheon and Chang, 1993; Bartal et al., 1995), and smart sensing (or function approximation) (Park et al., 2014a, 2014b; Na et al., 2008b). In the present study, the cascaded fuzzy neural network (CFNN) model is used to predict hydrogen concentration. The CFNN model presents the prediction value of hydrogen concentration through a repeatedly performed analysis using serially connected FNN modules. In effect, CFNN is an extended concept of FNN (Kim et al., 2015b).

The loss of coolant accident (LOCA) break size can accelerate propagation speed from LOCA to a severe accident (if safety systems do not work). Therefore, the LOCA break size is related to hydrogen generation rate versus time and related to hydrogen concentration trend released into containment. Because the proposed CFNN model predicts the hydrogen concentration in containment versus time, the LOCA break size is used as an input signal. The LOCA break size cannot be measured, but it can be predicted using the trend data for a short time after reactor trip. The LOCA break size can be accurately predicted using previously developed methods (Na et al., 2004, 2008a) and can be used as a variable input to predict the hydrogen concentration in the containment.

The CFNN model is a data-based method that requires data for its development and verification. Because real severe accident data cannot be obtained from actual NPP accidents, the data were obtained by numerically simulating severe accident scenarios of the optimized power reactor (OPR1000) using MAAP4 code (Henry et al., 1990).

2. CFNN model

The CFNN model structure contains serially connected FNN modules. The CFNN model predicts an appropriate value of the variable data through an analysis repeatedly performed by the serially connected FNN modules. A typical diagram of the CFNN model is shown in Fig. 1 (Kim et al., 2015b).

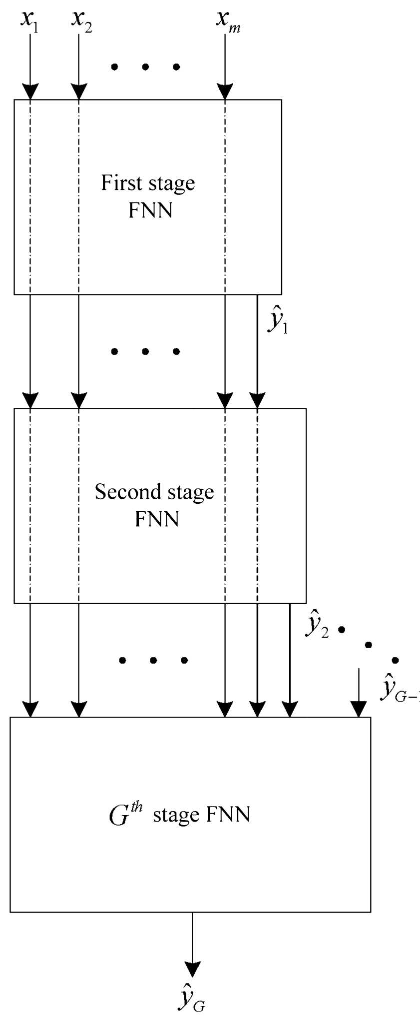

Fig. 1. CFNN model.

2.1. FNN model

The FNN model is a combination of a fuzzy inference system (FIS) and neuronal training. The conditional rule of FIS is applied by a fuzzy *if–then* rule that consists of an antecedent and a consequence (Mamdani and Assilian, 1975). The current study uses the Takagi–Sugeno-type FIS (Takagi and Sugeno, 1985) because it does not need a defuzzifier in the output terminal, which is a real value.

$$\begin{aligned}&\text{If }\ x_1(k)\ \text{ is }\ A_{i1}\ \text{ AND}\ldots\text{AND }\ x_m(k)\ \text{ is }\ A_{im},\\ &\quad\text{then }\ \hat{y}^i(k)\ \text{ is }\ f^i(x_1(k),\ldots,x_m(k))\end{aligned} \tag{1}$$

where $x_j(k)$: FIS input value ($j=1, 2, \ldots, m$), A_{ij}: fuzzy set for the i^{th} fuzzy rule and the j^{th} input variable ($i=1, 2, \ldots, n$), $\hat{y}^i(k)$: i^{th} fuzzy rule output, m: number of input variables and n: number of fuzzy rules.

The number of N_t input and output training data of the fuzzy model in Eq. (2) are assumed to be available, and each of the data is assumed to be a normalized value.

$$\mathbf{z}^T(k) = \left(\mathbf{x}^T(k), \hat{y}(k)\right) \tag{2}$$

where

$$\mathbf{x}^T(k) = (x_1(k), x_2(k), \ldots, x_m(k))\,, \quad k = 1, 2, \ldots, N_t.$$

The membership function of fuzzy sets $A_{ij}(k)$ is denoted as $\mu_{ij}(x_j(k))$. In this study, the symmetric Gaussian membership function in Eq. (3) is used to reduce the number of parameters to be optimized. It has a characteristic symmetric bell curve shape that tends to zero.

$$\mu_{ij}(x_j(k)) = e^{-(x_j(k)-c_{ij})^2/2\sigma_{ij}{}^2} \tag{3}$$

where c_{ij}: center position of the peak and σ_{ij}: width of the bell shape.

The membership function parameters are called antecedent parameters that should be optimized. The function in Eq. (1), namely, $f^i(x(k))$, is expressed as a first-order polynomial of the input variables, i.e., the output of each rule is expressed as follows:

$$f^i(\mathbf{x}(k)) = \sum_{j=1}^{m} q_{ij}x_j(k) + q_{i0} \tag{4}$$

where q_{ij}: weight of the i^{th} fuzzy rule and j^{th} input variable and q_{i0}: bias of the i^{th} fuzzy rule.

The output $\hat{y}(k)$ of FIS is calculated by summing the weighted fuzzy rule outputs $\hat{y}^i(k)$ as follows:

$$\hat{y}(k) = \sum_{i=1}^{n}\hat{y}^i(k) = \sum_{i=1}^{n}\bar{w}^i(k)y^i(k) = \sum_{i=1}^{n}\bar{w}^i(k)f^i(\mathbf{x}(k)) \tag{5}$$

where:

$$\bar{w}^i(k) = \frac{w^i(x(k))}{\sum_{i=1}^{n} w^i(x(k))} \tag{6}$$

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