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Original Article

PREDICTION OF HYDROGEN CONCENTRATION IN CONTAINMENT DURING SEVERE ACCIDENTS USING FUZZY NEURAL NETWORK

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ABSTRACT

Recently, severe accidents in nuclear power plants (NPPs) have become a global concern. The aim of this paper is to predict the hydrogen buildup within containment resulting from severe accidents. The prediction was based on NPPs of an optimized power reactor 1,000. The increase in the hydrogen concentration in severe accidents is one of the major factors that threaten the integrity of the containment. A method using a fuzzy neural network (FNN) was applied to predict the hydrogen concentration in the containment. The FNN model was developed and verified based on simulation data acquired by simulating MAAP4 code for optimized power reactor 1,000. The FNN model is expected to assist operators to prevent a hydrogen explosion in severe accident situations and manage the accident properly because they are able to predict the changes in the trend of hydrogen concentration at the beginning of real accidents by using the developed FNN model.

1. Introduction

Recently, severe accidents in nuclear power plants (NPPs) have become a global concern. In the event of severe accidents, the major safety parameters of nuclear reactors change rapidly during the initial stages, leaving operators with insufficient time to devise an appropriate response. The efficient management of a serious accident requires observation of the key parameters during the very brief duration of initial events by establishing scenarios and initial events leading up to the accident. In particular, it is extremely important to determine safety-related parameters and critical information during the extremely short period following a loss of coolant accident (LOCA) and steam generator tube rupture (SGTR). This would enable verification of NPP status and determination of appropriate corrective action.

In case of severe accidents, the NPP operators are concerned about hydrogen explosion due to hydrogen accumulation in containment. Hydrogen is accumulated in containment by leakage from the primary pressure boundary.

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Therefore, this work considered severe incidents that were caused by LOCAs, which were analyzed by using data from optimized power reactor 1,000 (OPR1000). The work aimed to predict the hydrogen concentration in the event of a severe accident. The increase in the hydrogen concentration is one of the factors threatening the integrity of the containment. The hydrogen inside the containment is generated by the radioactivation of water in the atmosphere, corrosion of the inner material of the containment by containment spray, and reaction of steam with the zirconium cladding. Maintaining the integrity of the containment by preventing the hydrogen within from exploding would require the local hydrogen concentration to be retained below 4%.

Therefore, in this study, various artificial intelligence (AI) methods were examined to predict changes in the hydrogen concentration. It was determined that a method using a fuzzy neural network (FNN) was the most suitable for predicting the hydrogen concentration. A number of AI techniques have been applied successfully to a variety of research fields of nuclear engineering, such as signal validation [1–3], plant diagnostics [4–7], event identification [8–10], and smart sensing (or function approximation) [11–13]. Many of the previous works used fuzzy inference systems (FISs) and neural networks (NNs). Jang and Sun [14] demonstrated the functional equivalence between NNs and FISs in cases when the activation functions of the NNs and the membership function of the FIS are the same.

An FNN is a data-based model that requires data for its development and verification. As data from real severe accidents do not exist, it is necessary to use numerical simulations to obtain the required data for the proposed model. The FNN model was verified based on the NPP simulation data acquired using MAAP4 code [15]. The successful management of NPPs as a result of the ability to rapidly predict safety-critical parameters during real accidents could lead to the safekeeping of NPPs.

2. Fuzzy neural network

Fuzzy theory has been studied in an attempt to use a mathematical approach to prove the inaccuracy in human thoughts and actions. The FIS has been produced based on the concepts of intelligent *learning* and *inference*. An FNN model consists of an FIS combined with its neuronal training system.

2.1. Fuzzy inference system

FIS generally uses conditional rules that comprise the *if/then* rules of the antecedent part and consequent part, and it is one of the methods of AI [3]. Both the antecedent and consequent parts have membership functions capable of fuzzifying crisp values. In most cases, the Gaussian, triangular, trapezoid, and bell-shaped functions are used in the membership function formula.

Fig. 1 shows a pictorial sketch of the FIS principle [16]. The FIS output should be a real value that requires defuzzifying prior to forming the FIS output. Using a Takagi-Sugeno-type FIS that does not require the defuzzifier, an arbitrary *i*-th rule can be expressed as follows [17]:

$$\text{If } x_1(k) \text{ is } A_{i1}(k) \text{ AND } \cdots \text{ AND } x_m(k) \text{ is } A_{im}(k), \text{ then } \hat{y}_i(k) \text{ is } f_i[x_1(k), \cdots, x_m(k)] \tag{1}$$

where $x_j(k)$ is the input variable to the fuzzy inference model ($j = 1, 2, \ldots, m$; m is the number of input variables), $A_{ij}(k)$ is the membership function of the j^{th} input variable for the i^{th} fuzzy rule ($i = 1, 2, \ldots, n$; n is the number of rules), and $\hat{y}_i(k)$ is the output of the i^{th} fuzzy rule. In Equation 1, the function $f_i[x_1(k), \cdots, x_m(k)]$ represents a function of input variables. The membership functions of the fuzzy sets $A_{i1}, \cdots, A_{im}$ for the i^{th} fuzzy rule are denoted as $\alpha_{i1}(x_1), \cdots, \alpha_{im}(x_m)$, respectively.

The number of N input and output training data of the fuzzy model $\mathbf{z}^T(k) = [\mathbf{x}^T(k), y(k)]$ (where $\mathbf{x}^T(k) = [x_1(k), x_2(k), \cdots, x_m(k)]$ and $k = 1, 2, \cdots, N\alpha_{i1}$) were assumed to be available and the data point in each dimension was normalized. A Gaussian membership function was used because of the ability of this function to reduce the number of parameters to be optimized. Using a Takagi–Sugeno-type FIS, the output of the FIS can be expressed as follows [17]:

$$\hat{y}(k) = \sum_{i=1}^{n} y_{wi}(k) \tag{2}$$

where

$$y_{wi}(k) = \overline{w}_i(k) f_i[\mathbf{x}(k)] \tag{3}$$

$$\overline{w}_i(k) = \frac{w_i(x(k))}{\sum_{i=1}^{n} w_i(x(k))} \tag{4}$$

$$w_i(k) = \prod_{j=1}^{m} \alpha_{ij}(x_j(k)) \tag{5}$$

$$\alpha_{ij}(x_j(k)) = e^{-\frac{\left(x_j(k) - c_{ij}\right)^2}{2s_{ij}^2}} \tag{6}$$

In Equation 3, the function $f_i[x(k)]$ is expressed as the first-order polynomial of input variables for the i^{th} fuzzy rule, and the output of each rule is expressed as follows:

$$f_i[\mathbf{x}(k)] = \sum_{j=1}^{m} \beta_{ij} x_j(k) + b_i \tag{7}$$

where β_{ij} is the weight of the i^{th} fuzzy rule and the j^{th} input variable, and b_i is the bias of the i^{th} fuzzy rule.

Therefore, in this case the FIS is referred to as a first-order Takagi-Sugeno-type FIS, because in the arbitrary i^{th} fuzzy rule output, f_i is a real value and is expressed as the first-order polynomial for the inputs.

Fig. 2 shows the calculation procedure of the FIS. The first layer indicates the input nodes that directly transmit the

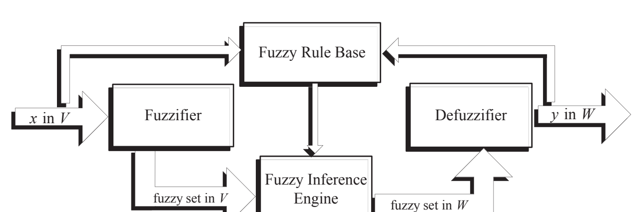

Fig. 1 – Fuzzy inference system (Mamdani-type).