Nuclear Engineering and Technology 48 (2016) 702–710

Available online at ScienceDirect

Nuclear Engineering and Technology

journal homepage: www.elsevier.com/locate/net

Original Article

# Reactor Vessel Water Level Estimation During Severe Accidents Using Cascaded Fuzzy Neural Networks

*Dong Yeong Kim, Kwae Hwan Yoo, Geon Pil Choi, Ju Hyun Back, and Man Gyun Na* *

*Department of Nuclear Engineering, Chosun University, 309 Pilmun-daero, Dong-gu, Gwangju 501-759, South Korea*

ARTICLE INFO

*Article history:*
Received 23 July 2015
Received in revised form
31 January 2016
Accepted 1 February 2016
Available online 23 February 2016

*Keywords:*
Cascaded Fuzzy Neural Network
Fuzzy Neural Network
Reactor Vessel Water Level
Severe Accident

ABSTRACT

Global concern and interest in the safety of nuclear power plants have increased considerably since the Fukushima accident. In the event of a severe accident, the reactor vessel water level cannot be measured. The reactor vessel water level has a direct impact on confirming the safety of reactor core cooling. However, in the event of a severe accident, it may be possible to estimate the reactor vessel water level by employing other information. The cascaded fuzzy neural network (CFNN) model can be used to estimate the reactor vessel water level through the process of repeatedly adding fuzzy neural networks. The developed CFNN model was found to be sufficiently accurate for estimating the reactor vessel water level when the sensor performance had deteriorated. Therefore, the developed CFNN model can help provide effective information to operators in the event of a severe accident.



## 1. Introduction

Global concern and interest in the safety of nuclear power plants (NPPs) have increased considerably since the Fukushima accident. In that severe accident, many of the functions of instrumentation and monitoring systems were lost and the plant operators could not monitor the important plant variables for plant safety [1].

Efficient management of a serious accident requires accurate observation of the key parameters (e.g., reactor vessel water level and hydrogen concentration) during the very brief elapsed time of the initial events in order to establish the scenario and determine the initial events that led up to the accident [1]. In particular, it is extremely important to determine the safety-related parameters and critical information during the extremely short period following a loss of coolant accident (LOCA) and steam generator tube rupture (SGTR).

The reactor vessel water level is essential information for confirming the cooling capability of the reactor core in order to prevent the core from melting down and effectively manage severe accidents. Proper measurement of the reactor vessel water level cannot be guaranteed in severe accidents where the reactor core integrity is uncertain. Therefore, estimating

* Corresponding author.
E-mail address: magyna@chosun.ac.kr (M.G. Na).
http://dx.doi.org/10.1016/j.net.2016.02.002

the reactor vessel water level is important to develop measures against severe accidents.

While physics-based models need detailed physical models of a plant that are difficult to derive, the data-based models of cascaded fuzzy neural network (CFNN) do not. Also, they can use a large number of NPP thermohydraulic code simulation results for safety analysis carried out extensively. However, the technique has the disadvantage that the estimation accuracy depends on the quality of the results retrieved from thermohydraulic code simulations that cover a wide range of plant operating conditions. Many artificial intelligence techniques have been successfully used in nuclear engineering applications, such as signal validation [2–4], plant diagnostics [5,6], and event identification [7–10]. This paper proposes a CFNN model to estimate the reactor vessel water level, which has a direct impact on important times (e.g., time before the core exit temperature exceeds 650 °C, core uncovery time, reactor vessel failure time) and is important for confirming the reactor core coolability.

The CFNN can be used to estimate the reactor vessel water level value through the process of repeatedly adding fuzzy neural networks (FNNs). The CFNN is a simple extension of FNNs. It has previously been applied to estimating the departure from nucleate boiling ratio [11] in nuclear engineering and is expected to provide superior performance. The LOCA break size and other measured signals are used to estimate the water level. The LOCA break size is not a measured variable; instead, it is estimated by using the trend data for a short time before an event that proceeds to a severe accident. The classification algorithm for determining the LOCA break position and LOCA break size estimation algorithm are explained in previous papers [12–15]. Because the LOCA break size can be accurately estimated by previously developed methods, the LOCA break size can be used as an input variable for estimating the reactor vessel water level.

The CFNN model is a data-based model that requires data for development and verification. Because real severe accident data do not exist, the data required by the proposed model need to be obtained by using numerical simulations. The data were obtained by simulating severe accident scenarios for the Optimized Power Reactor 1000 (OPR1000) by using modular accident analysis program (MAAP)4 code [16].

## 2. CFNN

The CFNN model contains two or more FNN modules. The CFNN estimates a relevant variable through the process of repeatedly adding an FNN. Fig. 1 shows the architecture of the CFNN model. Each FNN module contains fuzzification, fuzzy inference, and training units.

### 2.1. FNN module

The conditional rule, which is described as an *if–then* rule, is generally used in the fuzzy inference system (FIS). It comprises a pair: the antecedent and consequent [17]. In this study, the Takagi–Sugeno-type FIS [18] was used. This does not need a defuzzifier in the output terminal because its output is a real value.

In Eq. (1), an arbitrary $i^{th}$ fuzzy rule can be expressed as follows (first-order Takagi–Sugeno type):

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

where

$x_1,\cdots,x_m$: FIS input values
$m$: number of input variables
$A_{i1}(k),\cdots,A_{im}(k)$: fuzzy sets of the $i^{th}$ fuzzy rule
$y^i$: output of the $i^{th}$ fuzzy rule

The function $f^i(x_1(k),\cdots,x_m(k))$ is expressed by the following first-order polynomial of input variables:

$$f^i(x_1(k),\cdots,x_m(k)) = \sum_{j=1}^{m} q_{ij}x_j(k) + r_i \tag{2}$$

where

$q_{ij}$: weight of the $i^{th}$ fuzzy input variable
$r_i$: bias of the $i^{th}$ fuzzy rule.

Eq. (2) expresses a first-order Takagi–Sugeno-type FIS. $N_a$ input and output data $\mathbf{z}^T(k) = [\mathbf{x}^T(k), y(k)]$ $\{\mathbf{x}^T(k) = [x_1(k), x_2(k),\cdots,x_m(k)], k = 1, 2,\cdots, N_a\}$ are assumed to be available, and the input and output variables are normalized.

The membership function of the fuzzy sets $A_{i1}(k),\cdots,A_{im}(k)$ for the $i^{th}$ fuzzy rule is denoted as $\mu_{i1}(x_1),\cdots,\mu_{im}(x_m)$. In general, there is no special restriction on the shape of the membership functions. In this study, the symmetric Gaussian membership function was used to reduce the number of parameters for optimization:

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

The Gaussian membership function has a characteristic symmetric bell curve shape that falls towards zero. The parameter $c_{ij}$ indicates the center position of the peak, and $s_{ij}$ determines the width of the bell shape in Eq. (3).

The FIS output $\hat{y}(k)$ is calculated by weight-averaging the fuzzy rule outputs $y_i(k)$ as follows:

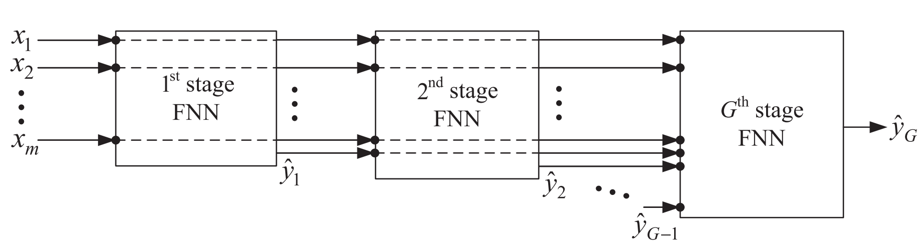


**Fig. 1 – Cascaded fuzzy neural network (FNN).**