Estimation of RV Water Level Using Deep Neural Networks under Severe Accident Circumstances in NPPs

Young Do Koo [a], Ye Ji An [a], and Man Gyun Na [a*]
[a]*Department of Nuclear Engineering, Chosun Univ., 309 Pilmun-daero, Dong-gu, Gwangju 61452, Korea*
[*]*Corresponding author: magyna@chosun.ac.kr*

1. Introduction

Acquiring the instrumentation signals from nuclear power plants (NPPs) is essential to assure the safety of the reactor under the normal operation condition or the accident circumstances. These instrumentation signals such as temperature, pressure, flow rate, H_2 concentration, and water level from the reactor, pressurizer, steam generator, containment, and so on are considered as safety-critical key parameters for the facilities and systems in NPPs. Therefore, the operators can properly control the plants and take necessary actions depending on the situations by diagnosing NPP states using these kinds of signals.

Among these signals, the reactor vessel (RV) water level is considered as one of the safety-critical parameters to keep the integrity of the primary system of NPPs. To be specific, the RV water level, which is directly related to determining the cooling capability for the nuclear fuel and preventing core uncovery, has a very important role to keep the safety of the primary system and even the whole NPP. In case of optimized power reactor (OPR) 1000, the RV water level is generally measured by heated junction thermocouple (HJTC) in the accidents [1].

However, the RV water level including other safety-related parameters can not be accurately measured due to the instrument inability or its uncertain integrity under the severe accident circumstances in NPPs. In this study, thus, the RV water level was estimated by applying other simulated signal and predicted signal data of NPPs to deep neural networks (DNNs) [2,3] under such circumstances in which the integrity of major instruments may not be ensured.

The DNN is generally with the supervised learning algorithms and accordingly, the data known as the actual or targeted values are needed. In this study, modular accident analysis program (MAAP) [4] was used to gain the simulation data for the assumed loss of coolant accidents (LOCAs) which may occur in NPPs.

2. A Deep Learning Method

The computing power is being enhanced owing to the continuously upgraded computer hardware and techniques and thus, well-known deep learning methods [3] has shown their outstanding performance for a variety of fields. As a deep learning method, the DNN used in this study can be defined as a multilayer neural networks with effective learning algorithms. In addition, the DNN can be considered as a straightforward network due to utilized activation function in its hidden layers and weight propagation flow than other deep learning methods such as recurrent neural network (RNN) and long-short term memory (LSTM) [3].

2.1 Deep Neural Networks

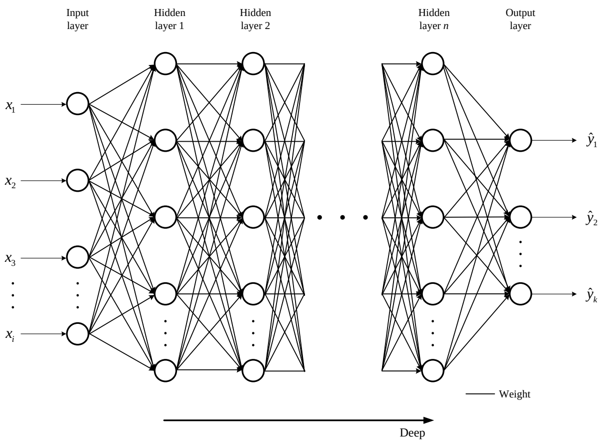

Fig. 1. Deep neural networks

The DNN is an artificial neural network with multiple hidden layers and nodes (refer to Fig. 1) and is occasionally called feedforward neural networks (FFNNs) or deep feedforward networks (DFNs) [3] due to the particular output flow between the nodes in each layer. In other words, the outputs, calculated from the each node in the input layer using input values $\boldsymbol{x}$ (refer to Fig. 2), are transferred forward and updated through the hidden layers, and finally the estimated values $\hat{y}$ are computed in the output layer.

The backpropagation (or backprop) [5,6] and gradient descent [3,6] algorithms are commonly used for learning and optimization of the DNN method.

Specifically, the error between the estimated value through feedforward and the targeted value is transferred backward from the output layer to the hidden layers. After then, the gradient is calculated and finally the weight w_{ij} is able to be updated using the backprop and gradient descent algorithms (refer to Fig. 3). It is noted that the gradient descent algorithm is a technique to approach the global minima, which is the lowest point of the cost function expressed in Fig. 4, by iteratively calculating the gradient of the cost function at the each current point.

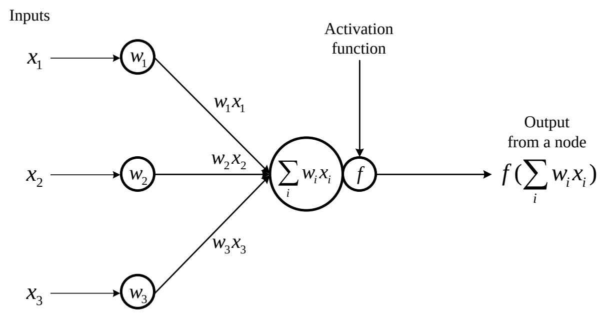

Fig. 2. An illustration of single artificial neuron.

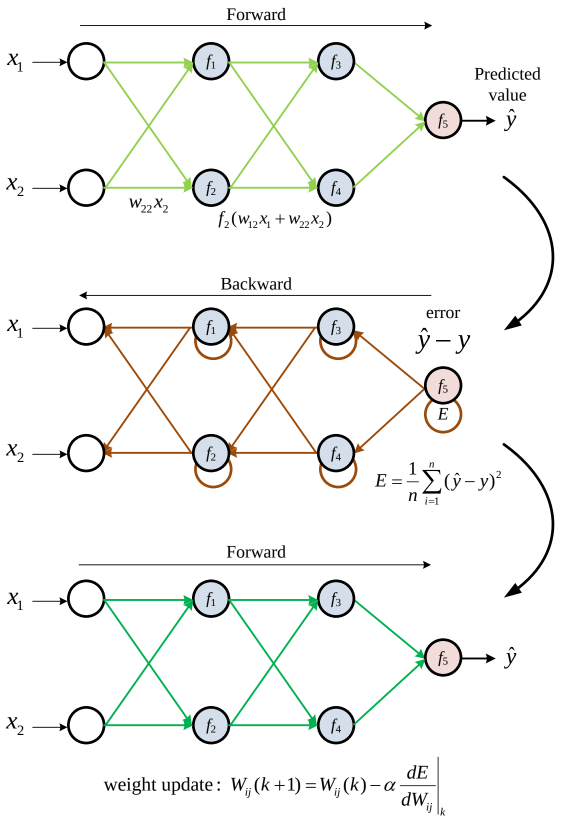

Fig. 3. Training and optimization procedure of the DNN.

The hypothesis of the DNN and the cost function for convex function are generally defined as Eqs. (1) and (2).

$$H(\boldsymbol{x}) = w_{ij}\boldsymbol{x} = \boldsymbol{W}\boldsymbol{x} \tag{1}$$

$$\mathrm{cost}(\boldsymbol{W}) = E = \frac{1}{n}\sum_{i=1}^{n}(\hat{y}_i - y_i)^2 \tag{2}$$

where $\hat{y}_i = (\boldsymbol{W}\boldsymbol{x})_i$ is the i-th estimated value and y_i is the i-th targeted value.

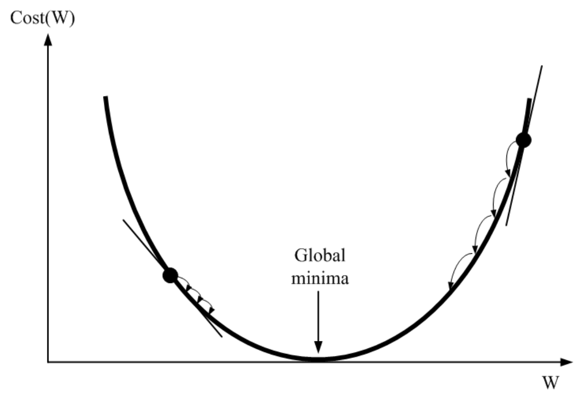

Fig. 4. Global minima in the cost function.

2.2 Optimization of DNN

It is known that the aforementioned DNN method can be more powerful by applying more data and making its hidden layers deeper. However, the DNN with an excessively deep structure can be vulnerable to the vanishing gradient and the overfitting problem [7].

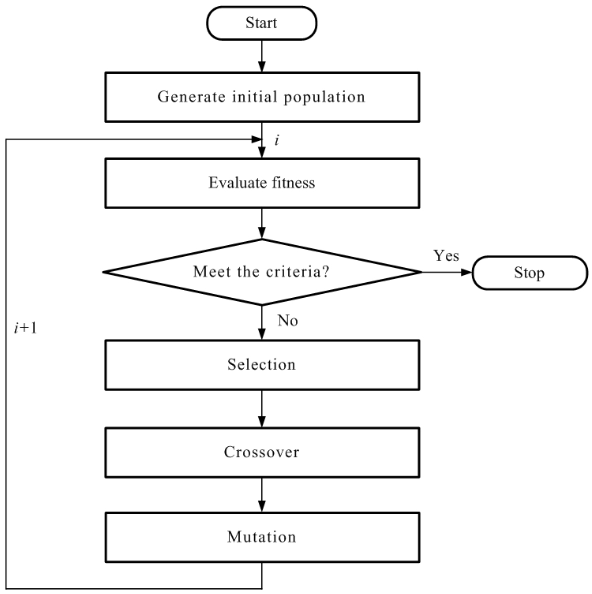

Fig. 5. Genetic algorithm process.

Therefore, the number of the hidden layers and nodes, as parts of the hyperparameters for the optimized performance of the DNN, was determined using another optimization technique, genetic algorithm (GA) [8,9] in this study.

Briefly, the GA employed in this study is a technique artificially modelling an evolutionary process of organisms by the natural evolution mechanisms such as selection, crossover, and mutation. Plus, the fitness function (refer to Eq. (3)) is needed to evaluate how fit the chromosomes are by assigning the scores to each population in GA. The GA process is described in Fig. 5.

$$F = \exp(\lambda_1 E_t + \lambda_1 E_v + \lambda_2 E_{\max \cdot t} + \lambda_2 E_{\max \cdot v}) \quad (3)$$

where λ_1 and λ_2 are weights for RMS and maximum errors for the training data (E_t and $E_{\max \cdot t}$) and the verification data (E_v and $E_{\max \cdot v}$) sets, respectively.

2.3 Employed DNN

Notwithstanding several techniques such as rectified linear unit (ReLU) function, dropout [10], and so on to solve the aforementioned vanishing gradient and overfitting problems, the initial hyperparameters of the DNN can be variable according to the subject.

Thus, a part of applied options for the DNN is shown in Table I. The number of the hidden layers and nodes was selected using the GA and the bipolar sigmoid function (defined as Eq. (4)) was used as the activation function of the DNN owing to the better performance than others' in this study.

$$f(x) = \frac{1 - \exp(-x)}{1 + \exp(-x)} \quad (4)$$

Table I: Applied hyperparameters for the DNN

Hyperparameters	Application
No. of hidden layers	Selected by the GA
No. of hidden nodes	Selected by the GA
Activation function	Bipolar sigmoid
Cost function	Mean squared error (MSE)

3. Applied Data and Estimation Performance

3.1 Data Component

The MAAP [4] was used to acquire the data applied to the DNN with the backprop and the gradient descent algorithms by simulating some of the various LOCAs. The assumed LOCAs were at three break positions (hot-leg, cold-leg, and steam generator tube (SGT)) and the break sizes were divided into small breaks and large breaks in each position.

These data from the MAAP code consist of simulated instrumentation signals for the various NPP parameters, numerically expressed. The applicable parameters to estimate the RV water level in the simulation data at each break position are predicted LOCA break size, containment pressure, and so on.

Although the predicted LOCA break size is considered easily non-recognizable under the actual accident circumstances, it was regarded as a signal to estimate RV water level in this study since the quite good prediction performances were shown in the past studies to predict the LOCA break size using the artificial intelligence methods [11]-[13].

3.2 Estimation Performance of DNN

The estimation result of the RV water level utilizing the proposed DNN model is expressed in Table II. The estimation performances for each data set, which is divided for literally 'training' and 'test', are expressed as root mean square error (RMSE). Moreover, to compare with the performance, the result of a previous study using the same signals applied to a machine learning method [1] is shown in Table III. According to Tables II and III, each method has outstanding performance for the RV water level estimation. However, the proposed DNN model has a slightly better performance for the test data in most cases.

Table II: Performance of the RV water level estimation using the DNN

Break size	Break position	Training data	Test data
		RMSE (m)	RMSE (m)
Small	Hot-leg	0.21	0.30
	Cold-leg	0.16	0.18
	SGT	0.21	0.19
Large	Hot-leg	0.07	0.04
	Cold-leg	0.17	0.38
	SGT	0.29	0.41

Table III: Performance of the RV water level estimation using the CFNN

Break size	Break position	Training data	Test data
		RMSE (m)	RMSE (m)
Small	Hot-leg	0.10	0.32
	Cold-leg	0.14	0.19
	SGT	0.29	0.22
Large	Hot-leg	0.03	0.07
	Cold-leg	0.09	0.14
	SGT	0.32	0.50

Fig. 6 is a graph indicating the estimation performance of the RV water level for the test data in case of small break LOCA at the cold-leg using the DNN. It is considered that the targeted RV water level is well tracked by the estimated RV water level.

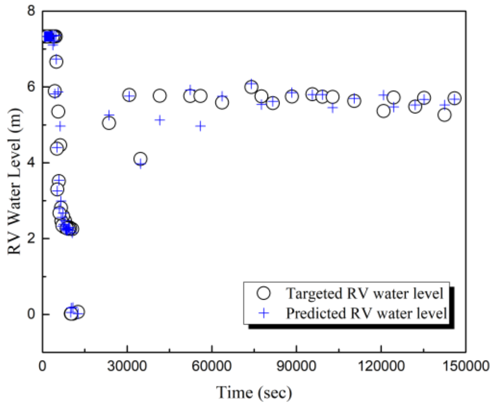

Fig. 6. Estimation of the RV water level for the test data at the cold-leg (small break LOCA).

4. Conclusions

In an effort to provide the supporting information to NPP operators, this study on the estimation of the RV water level using the DNN under the severe accident circumstances, when the integrity of the instruments can not be ensured, was carried out. The assumed LOCAs, originated in hot-leg, cold-leg, and steam generator tube, were simulated using the MAAP code to acquire the data for the RV water level estimation. These accident simulation data consist of the numerically expressed behaviors of the several signals.

The applied signals to the proposed DNN model were the predicted LOCA break size and containment pressure. The outstanding estimation performance for the RV water level of the DNN has been shown in spite of only two signals applied. Therefore, the DNN model can be considered as a method to accurately estimate the RV water level employing other signals under the severe accident circumstances.

Furthermore, although it is known that the proper hyperparameter setting, known as a golden rule, has yet to be established, the DNN with the optimized hidden layers and nodes, selected by the GA in this study, has been slightly better than the machine learning method [1].

Consequently, it is expected that the result of this study can be a case study to estimate the key parameters using the DNN in NPPs in the future.

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