# Hydrogen Concentration Prediction and Hydrogen Explosion Threat Determination in Severe Accidents

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## 1. Introduction

In the event of a severe accident in nuclear power plants (NPPs), if the reactor cannot be cooled and the heat is not removed, the reactor core can be melted. A metal such as zirconium used as a fuel covering material is oxidized with high temperature steam to generate a large amount of hydrogen. The generated hydrogen is released into the containment building and if the hydrogen concentration is more than 4% of the volume of the air inside the containment building, a hydrogen explosion may occur, which threatens the integrity of the containment. The hydrogen is very explosive, and when an explosion occurs, it damages multiple defense walls and a large amount of radioactive material is released outside the containment. Therefore, it is important to predict the concentration of hydrogen generated in the melted core in severe accidents.

Since it is limited to obtain the accident data of nuclear power plants, Modular Accident Analysis Program4 (MAAP4) code [1] for optimized power reactor 1000 (OPR1000) was used. The initial conditions of MAAP simulations were simulated according to whether or not the Passive Autocatalytic Recombiner (PAR) was operated. In addition, the data obtained from the MAAP were analyzed against the hydrogen threat by comparing with the Severe Accident Management Guideline (SAMG) calculation table for OPR1000.

In this study, the hydrogen concentration under severe accidents caused by Loss of Coolant Accidents (LOCAs) was predicted by using only limited measurement signals using Deep Neural Network (DNN), one of the artificial intelligence methods. [2]

If the reactor operators can use the DNN model to predict quite accurate hydrogen concentration within containment in case of severe accidents, it will help them prevent the hydrogen explosion.

## 2. Deep Neural Network

Deep learning is a methodology based on the Artificial Neural Network (ANN) algorithm that mimics the overlap of synapses in the human brain structure. Nowadays many researchers are considerably interested in the deep learning algorithm which provides excellent performance with large data sets. Fig. 1 is a deep neural network (DNN), which models complex nonlinear relationships using multiple hidden layers of units between the input and output layers. [3]

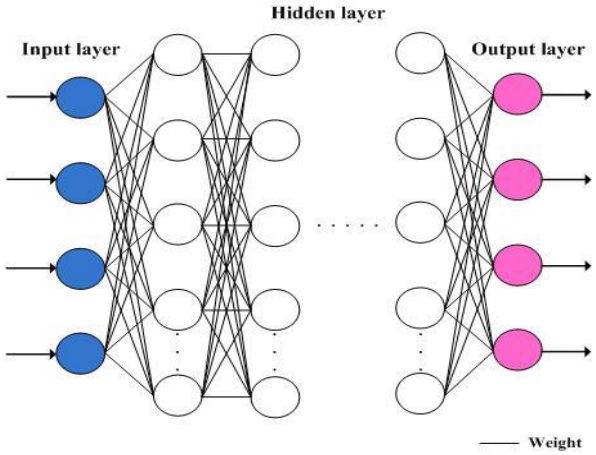


Fig. 1. Deep Neural Network (DNN) model

In the learning process of the DNN model, the node output values of the hidden layer calculated through the activation function reach the output layer and the predicted value is calculated. The weight values are optimized using an error backpropagation method. Equations (1) and (2), respectively, present a cost function and updated weight values. This learning is repeated until the global minima, the lowest point in the cost function, is reached, as shown in Fig. 2 [2].

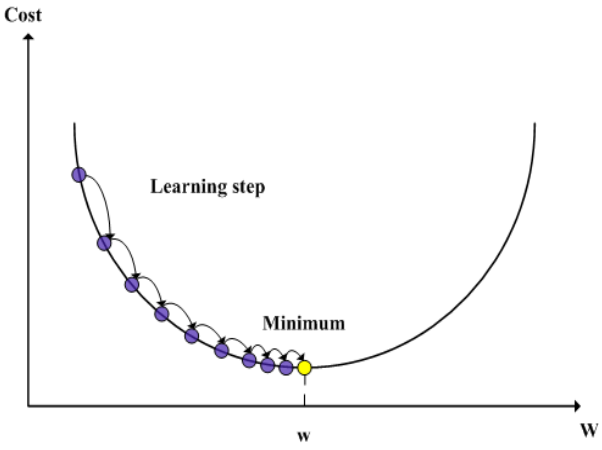


Fig. 2. Gradient Descent

$$Cost(\boldsymbol{W}) = E = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(\hat{y}_i - y_i)^2} \quad (1)$$

$$w_{ij}^{new} = w_{ij}^{old} - \alpha \frac{dE}{dw_{ij}} (0 < \alpha < 1) \quad (2)$$

The DNN model, which has an excessively deep structure, can experience vanishing gradient phenomenon with a backpropagation algorithm and may be vulnerable to overfitting problems. [4]

First, the overfitting problem can be resolved through cross validation using the data structure shown in Fig. 3. Data applied to the DNN is divided into the training data sets and validation data sets related to model development, and test data sets independent of learning. [5]

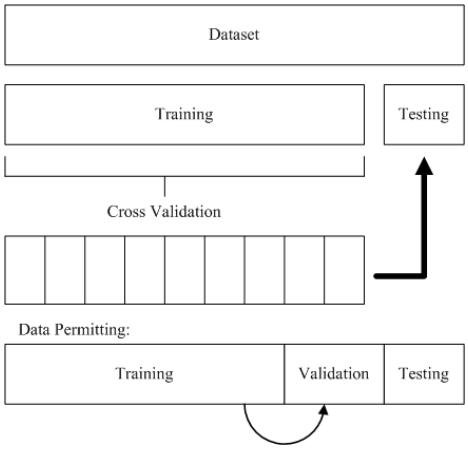


Fig. 3. Cross Validation

After the model is trained for each epoch, the validation data is used to measure the error of the model and the error of the validation data is minimized when the model is learned optimally. The DNN learning in this study is repeated until the cost(W) converges to the global minima or until the maximum number of epochs is reached.

Second, a solution to the vanishing gradient is the use of the bipolar sigmoid function as the activation function. The problem of vanishing gradient is, that if the activation function is sigmoid as shown in Fig. 4, the graph for the output value becomes flat after a lot of learning and the gradient approaches zero. As a result, the error is hardly transmitted to the hidden layer in front, resulting in a phenomenon that the hidden layer weights are not properly learned.

Therefore we use the bipolar sigmoid function as shown in Fig. 5, which is less sensitive to vanishing gradient than the sigmoid function. In spite of the well-known ReLU function, which is known for its excellent performance in many studies, the bipolar sigmoid has shown that optimal performance is obtained under the same data conditions applied to the proposed model.

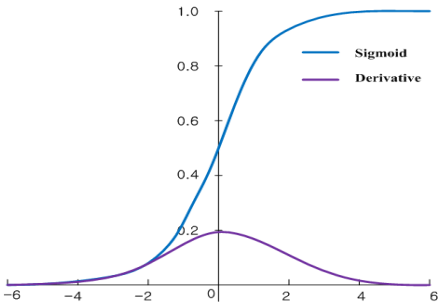


Fig. 4. Sigmoid and its Derivative Functions

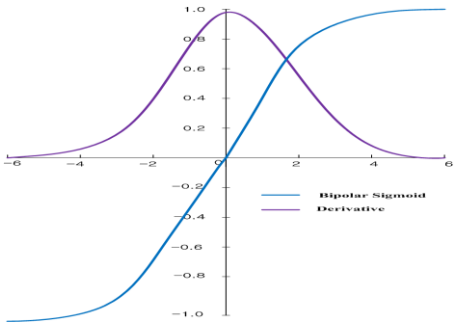


Fig. 5. Bipolar Sigmoid and its Derivative Functions

## 3. Hydrogen Concentration Threat Determination

The relationship between containment building pressure and hydrogen concentration for the parameter input values used for MAAP4 is compared with the Severe Accident Management Guideline (SAMG) calculation table. Fig. 6 is quoted from the OPR1000 nuclear power plant SAMG calculation table-02.

Figs. 7-10 show the predicted hydrogen concentration using the DNN method. In case of PAR OFF, at each break size, the hydrogen concentration is estimated to be about 1% higher than when PAR is activated.

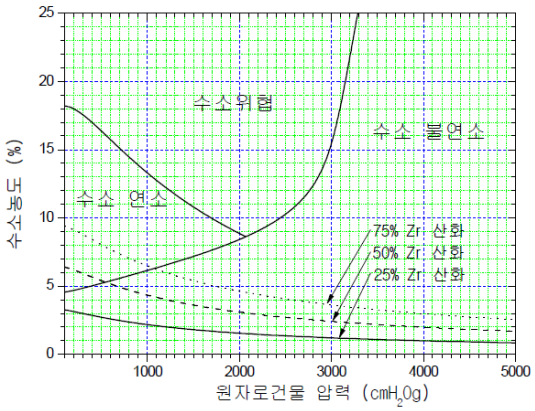


Fig. 6. Possibility of Hydrogen Combustion (No Vent, No CCI, wet hydrogen measurement)

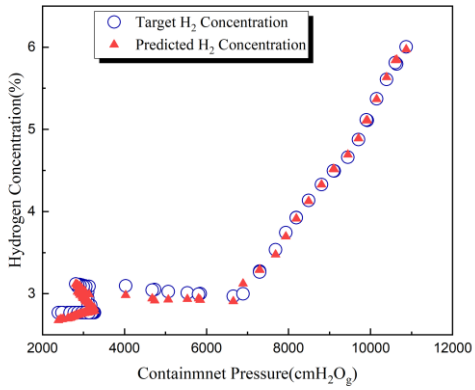


Fig. 7. Hydrogen Concentration for Containment Building Pressure (In case of PAR OFF, small cold-leg LOCA)

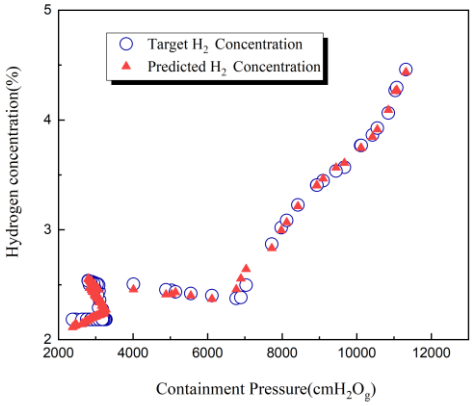


Fig. 8. Hydrogen Concentration for Containment Building Pressure (In case of PAR ON, small cold-leg LOCA)

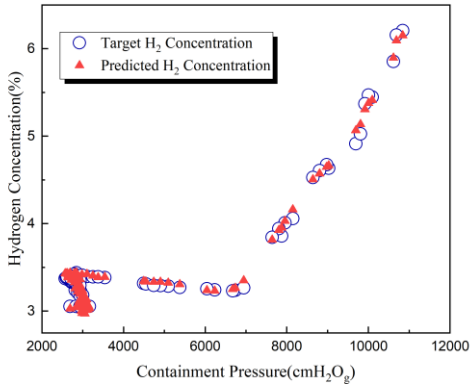


Fig. 9. Hydrogen Concentration for Containment Building Pressure (In case of PAR OFF, large cold-leg LOCA)

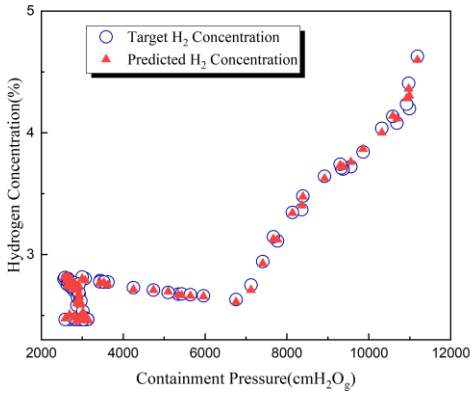


Fig. 10. Hydrogen Concentration for Containment Building Pressure (In case of PAR ON, large cold-leg LOCA)

## 4. Application to Predicting the Hydrogen Concentration

The data simulating LOCAs situations at cold-leg location is obtained using MAAP, which can simulate the overall system response to all types of accidents, such as LOCA at nuclear power plant. And the simulation data is applied to the DNN method to check the hydrogen concentration prediction performance. Only limited signals of predicted LOCA break size and hydrogen is used as input for hydrogen concentration prediction

The performance of the hydrogen concentration prediction using the DNN model is verified by RMSE. The RMSE shows considerably low level for cold-leg LOCA location and break sizes (refer to Table I). It proves that the DNN model has a good performance.

Table I. Prediction performance of the DNN model at cold-leg

| PAR | Break size | RMS error (%) | |
|---|---|---|---|
| | | Training data | Test data |
| OFF | Small | 0.19 | 0.25 |
| | Large | 0.06 | 0.10 |
| ON | Small | 0.14 | 0.23 |
| | Large | 0.12 | 0.16 |

Additionally, the result of this study can be compared with previous studies on the hydrogen concentration prediction using the models based on Fuzzy Neural Network (FNN) [6] and Cascaded Fuzzy Neural Network (CFNN) [7].

## 5. Conclusions

It is important to predict the hydrogen concentration at severe accidents. It is essential to prevent threats due to hydrogen combustion and explosion before the hydrogen concentration in the containment exceeds 4%.

In order to reduce the possibility of hydrogen explosion, we have developed and tested a method for predicting the hydrogen concentration using the DNN model. The input data applied to the DNN model used only limited signals, which are the variables for the elapsed time after the reactor shutdown, the predicted LOCA break size, and the containment pressure.

In this study, the DNN model has a low RMS error at all break locations and can accurately predict hydrogen concentration in containment and can provide operators with a trend of hydrogen concentration change in the containment after a LOCA. The proposed DNN model will be helpful for operators to maintain the integrity of NPPs due to hydrogen threat.

## REFERENCES

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