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Development of Prediction Models for Spent Nuclear Fuel Storage Cask Monitoring

Hyong Chol Kim*, Sam Hee Han, Dong Jae Park
NSE Technology Inc., 5F Convergence Technology Research Commercialization Center
218 Gajeong-ro, Yuseong-gu, Daejeon, 34129, Korea
**Corresponding author: hckim@nsetec.com*

1. Introduction

More than 1500 spent nuclear fuel (SNF) dry storage casks have been installed at commercial nuclear power plant sites in the United States [1]. The storage term of SNF in dry storage casks has been sought to extend due to continued delays in establishing permanent disposal facilities in most countries that operate nuclear power plants. As the storage terms of SNF are extended, aging management and monitoring issues become progressively more important for ensuring the safe operation of the dry storage casks.

Variety of technologies are in use for confinement monitoring of SNF dry storage systems [2]. Recently, a method based on surface temperature measurements has been developed for detecting helium gas leak from canister [3] and the canister surface temperature (CST) has been studied as a means to detect helium leakage from a breach of a welded canister due to aging degradation [4]. It would be beneficial in that canister internal pressure can be monitored without any pressure sensor line penetration through the canister wall.

In this study, a canister monitoring method using neural network models is proposed to monitor the canister internal pressure and the peak cladding temperature (PCT) based on the canister surface temperature of the SNF storage cask.

2. Experimental Analysis and Results

Vertical dry storage casks are predominantly two types: a metal cask using a bolted lid or a welded steel canister inside a concrete overpack [5]. A test apparatus has been constructed to investigate thermal behaviors of the vertical dry storage cask with reference to the domestic design of storage cask having a metallic canister with separate concrete overpack [6].

The main purposes of the test apparatus are to analyze relationships between the state parameters such as the internal pressure, PCT, and CSTs and to verify the methodology proposed for monitoring application.

2.1 Description of Test Apparatus

The test apparatus is scaled-down with 1/3 height of the reference design and loaded with a single 16x16 fuel assembly. The fuel rods are simulated by electric heaters with a power supply which allows variation of decay heat to achieve the appropriate operating thermal state. The fuel assembly is composed of 236 rods and enclosed by a basket. The canister containing the fuel assembly is filled with helium gas. Downflows are formed through the holes of support disks installed between the basket and the canister shell due to natural convection of helium in the canister. Upward air flow is caused in the annular gap between the canister and the concrete simulant.

As shown schematically in Fig. 1, the test apparatus is provided with temperature sensors for fuel rod cladding temperature, inlet and outlet air temperatures, and cannister surface temperature measurements.

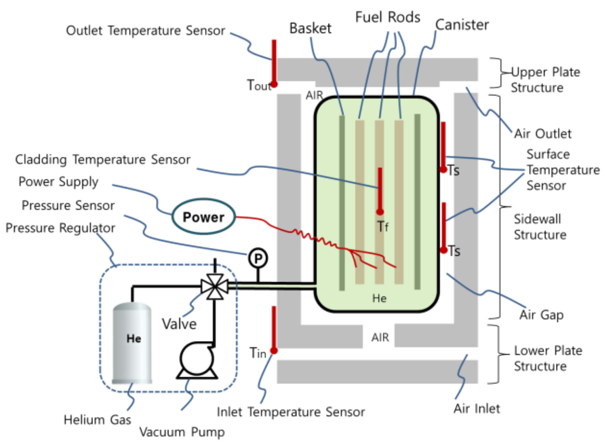

Fig. 1. Schematic diagram of test apparatus.

Fig. 2. Perspective photo of test apparatus.

Fuel temperature sensors are attached to six fuel rods along the diagonal and transverse directions in the fuel assembly, as shown in Fig. 3, at five axial levels corresponding to 10%, 30%, 50%, 70%, and 90% of the active fuel length. Serial numbers are assigned to fuel rods from the top left to the bottom right and six of them attached with sensors are indicated in Fig. 3.

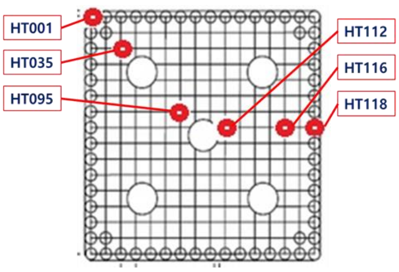

Fig. 3. Sensor-attached rods in fuel assembly.

Surface temperature sensors are attached to the canister surface positions at the four axisymmetric directions as shown in Fig. 4 and axially at the same five axial levels.

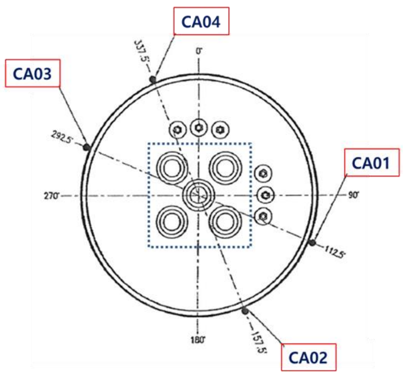

Fig. 4. CST measurement positions on the canister.

The test apparatus is also provided with a pressure sensor and the helium gas pressure regulator which can simulate helium gas leak from the canister.

All the sensor measurements are recordable with a multi-channel data acquisition unit for detailed data reviews.

2.2 Results of the Tests

Experimental conditions were chosen to obtain PCT in the range of 300℃ to 400℃. Ambient air temperature was maintained in the range of 21℃ to 34℃.

Two series of pressure varying tests were carried out with electric powers of 1.60 kW and 1.72 kW.

Helium pressure was varied between about 0.35 MPa and 0.01 MPa with fixed electric powers and 11 steady-states were selected for the database for the neural network prediction model development which is described below.

Fig. 5 shows an example of the cladding temperature axial profiles of the fuel rods with electric power of 1.60 kW at helium pressure of 0.155 MPa. As shown in the figure, the cladding temperature gradually increases from the assembly periphery to the central region both in the diagonal and transverse directions. The peak temperature occurs at the 4-th level of the central rods in this case.

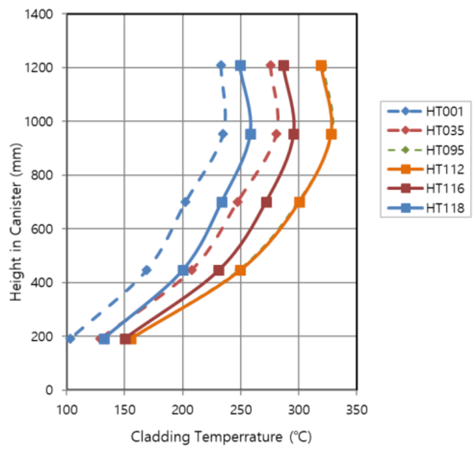

Fig. 5. Cladding temperature profiles of fuel rods.

Fig. 6 shows the cladding temperature variation of the central rod HT095 when the helium pressure is decreased with electric power of 1.72 kW. It is observed that the peak cladding temperature increases and the position of peak temperature shifts toward the assembly center as the helium pressure decreases. This result was as expected because heat conduction and convection in the canister become less active when the helium pressure becomes lower so that helium density is lowered.

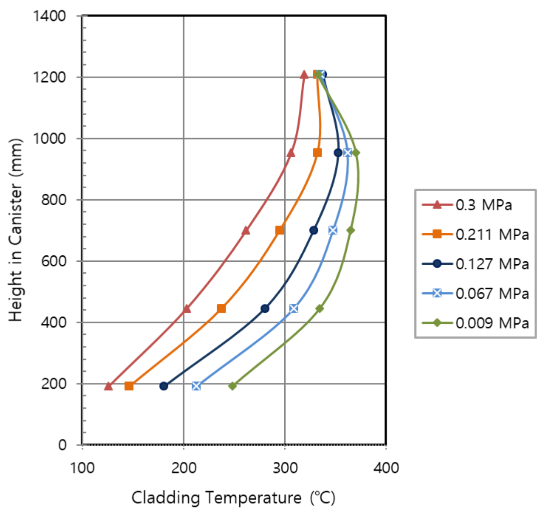

Fig. 6. Cladding temperature variation as a function of helium pressure.

Fig. 7 shows the canister surface temperature (CST) variation at circumferential position CA02 on the canister shell at pressure conditions corresponding to the cladding temperature variation shown in Fig. 6. It is observed that CST increases with varying profiles as the helium pressure decreases.

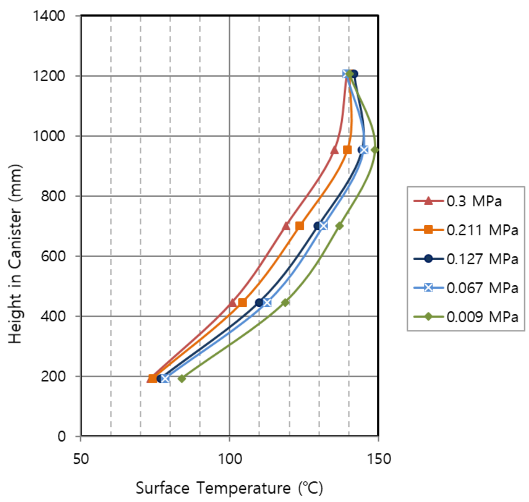

Fig. 7. CST variation as a function of helium pressure.

3. Development of Neural Network Prediction Models

It is important to make sure that initial helium gas is confined without leak to keep the maximum fuel cladding temperature within the design limit during the extended long-term operation of dry storage casks. For the purpose of confinement monitoring, the internal pressure and PCT prediction models were developed using neural networks using CST information as input.

3.1 Description of Neural Network Models

For prediction of the internal pressure and the PCT, correlations between the internal pressure and CSTs and between PCT and CSTs need to be established. The correlations were established by neural network models using the delta rule with the backpropagation algorithm [7].

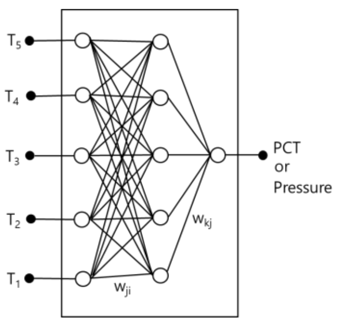

Fig. 8. Schematic depiction of neural network model.

As shown in Fig. 8, a fundamental 3-layered neural network was employed. Input variables are CSTs at the five axial levels as explained in Section 2.1 and output variable is the PCT or the canister internal pressure. Weight vectors, w_{ji} and w_{kj}, that define synaptic connectivity between nodes are to be determined through the iterative learning process of back-propagation algorithm.

Since the dependency characteristics of the PCT and the internal pressure on the CSTs are quite different, neural network models were developed separately for the PCT and the internal pressure. In case of the pressure prediction network model, temperature slopes derived from CSTs were added as functional-link inputs to improve prediction performance.

3.2 Training Results of Neural Network Models

Database for training neural network models by supervised learning was built from 11 steady-state test points as explained in Section 2.2.

At the termination of training of the PCT prediction network, the standard deviation was 2.0℃ and the maximum deviation was less than 6℃. Fig. 8 shows the PCT prediction results of training graphically.

At the termination of training of the pressure prediction network, the standard deviation was 0.0035 MPa and the maximum deviation was less than 0.01 MPa. Fig. 9 shows the pressure prediction results of training graphically.

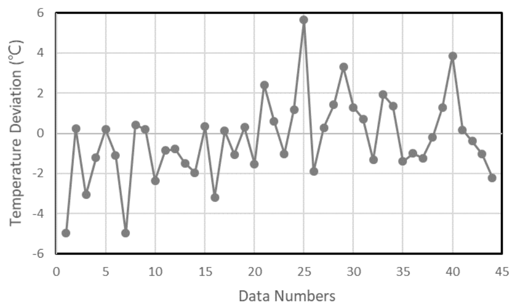

Fig. 8. Training results of PCT prediction deviation.

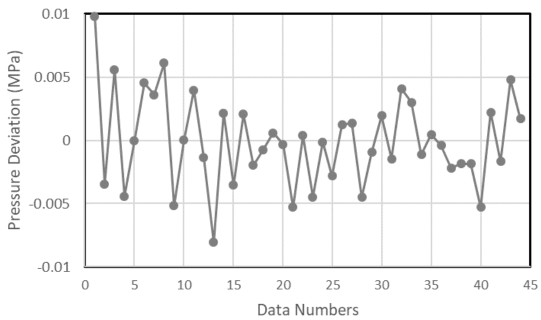

Fig. 9. Training results of pressure prediction deviation.

4. Results of Monitoring Application

Since the prediction models for PCT and internal pressure have been determined as explained in Section 3.2, the prediction models were applied to the actual test data for verification as a means of monitoring method for dry storage casks.

The pressure varying test with electric power of 1.72 kW explained in Section 2.2 was conducted for about 18 days with internal pressure variation from around 0.35 MPa to 0.01 MPa.

Fig. 10 shows the monitored pressure using the neural network pressure prediction model compared with the actual measurement data for the above test case. The pressure variation of Fig. 10 presents fictitious transients caused by abrupt pressure drops and quasi-steady states between the transients.

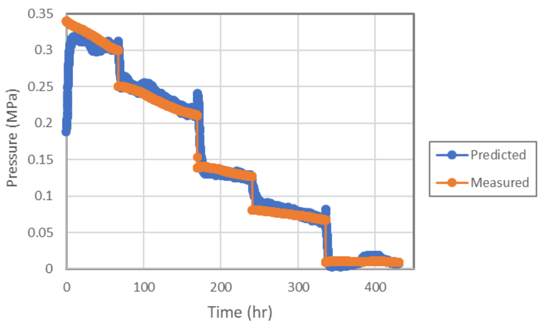

Fig. 10. Monitoring results of canister internal pressure.

Fig. 11 shows the monitored peak cladding temperature using the neural network PCT prediction model compared with the actual measurement data.

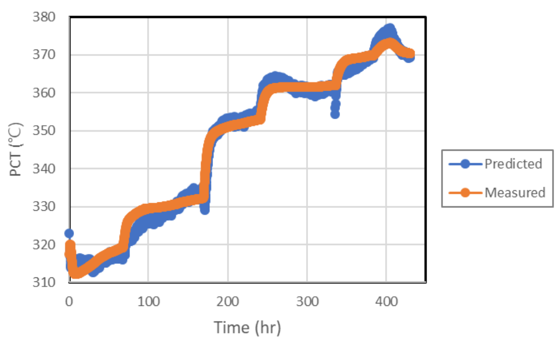

Fig. 11. Monitoring results of peak cladding temperature.

The prediction results of the monitoring models were relatively excellent for both pressure and PCT when the thermo-fluidic state becomes stabilized after transients. The monitoring model could easily alarm any transient occurrence due to rapid helium gas leak when abnormal peaks or drops are observed in the internal pressure and the peak cladding temperature.

It is noted that both prediction and measurement are unreliable due to unstable conditions at the initial period of the test.

5. Conclusions

A test apparatus was constructed to investigate thermal behaviors of the vertical dry storage casks. Series of tests have been conducted to build database for training neural network prediction models for monitoring application. Training database was built from steady-state points of the tests.

Prediction models were developed using neural networks which use axially aligned canister surface temperatures as input parameters.

The prediction results of the developed models have been found to be relatively excellent for stabilized thermo-fluidic states. And thermo-fluidic transients caused by rapid pressure loss could be easily alarmed from anomaly indication of the prediction models.

Therefore, the neural network prediction models can predict the canister internal pressure and the PCT based on the canister surface temperatures without any pressure gauge installation and appear promising for confinement monitoring of dry storage casks.

In the future, steady state CFD simulation for model training database is needed for practical application of this study.

ACKNOWLEDGMENTS

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