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Applications of Neural Network to Predict Reactor Vessel Failure Time for Various Component Failures during Severe Accident

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1. Introduction

After the Fukushima accident, the management of a severe accident becomes more important to prevent severe core damage, core melting, and consequential radiation leakage. Since the uncertainty in the severe accident progression is too large, a guideline rather than a procedure, so-called severe accident management guideline (SAMG) is provided for the accident management. According to the SAMG, when a severe accident occurs, the technical support center (TSC) is formed to evaluate a positive or negative impact of various mitigation strategies based on the current status of the nuclear power plant (NPP) and the available systems, and to determine an optimal strategy for the accident mitigation. However, in such a dangerous and rapidly changing accident situation, making a decision in a short time can cause a lot of burden and stress to the TSC staff and lead to human error. Therefore, the accident management support tool (AMST) is required to assist decision making during the accident situation [1].

The major functional requirements of the AMST are as follows:

1) Track the current status of the NPP.
2) Predict the accident progress for various accident mitigation strategies.
3) Search for the optimal mitigation strategy based on the numerous prediction calculations.

Various AMSTs have been developed, such as MARS [2] and SAMEX [3]. These AMSTs use the severe accident analysis code or accident database for predictive calculations. The severe accident analysis code can accurately predict the consequence of the accident progress, but it takes a long computing time. On the other hand, the accident database based on the probabilistic safety assessment (PSA) takes very short computing time. However, it requires many prediction calculations via severe accident analysis code to build the database, and only scenarios in the PSA can be treated.

Therefore, a soft computing method for the predictive tool is required that can quickly calculate the accident consequence for various scenarios and mitigation strategies with acceptable accuracy. In the previous study, Na et al. (2004) applied the neural network to classify the accident scenarios and predict the timing of major events [4]. In this preliminary study, the authors apply a neural network to predict the reactor vessel failure time for various component failure cases.

2. Methods

2.1 Selection of Accident Scenario

The total loss of component cooling water (TLOCCW) accident was selected to confine the list of failed component candidates. In the TLOCCW accident scenario, the safety-related equipment such as an emergency diesel generator and shutdown heat exchanger (HX) is not available due to the loss of the component cooling water. In addition, the pump seal cooling failure occurs first, and this is followed by losses of the high pressure safety injection (HPSI), the low pressure safety injection (LPSI), the charging pump (CHP), the containment spray system (CSS), and the motor-driven auxiliary feedwater (MDAFW). The seal of the reactor coolant pump (RCP) is also not cooled, so RCP seal loss of coolant accident (RCP seal LOCA) occurs. During the TLOCCW accident scenario, 7 components those can be failed were selected as shown in Table I. Other engineered safeguards were assumed to operate passively.

Table I Components those can be failed during TLOCCW accident scenario

Component Name
RCP seal LOCA
HPSI
LPSI
CHP
CSS
MDAFW
HX

2.2 Data production via MAAP 5.03

A total of 559 accident scenario input files were prepared and simulated via MAAP 5.03. The MAAP 5.03 is the severe accident analysis code developed by EPRI[5]. OPR1000 is the target nuclear power plant for this analysis. During the 72-hour accident time, the failure time of the components in Table I was discretely sampled with 1-hour intervals. Each failure probability is 0.5, so frequency distribution of the number of the failed components is expected to follow Poisson distribution as shown in Fig. 1. The failure time is assumed as a uniform probability density function (PDF) except for the RCP seal LOCA. The failure time for the RCP seal LOCA was sampled from the log-normal distribution [6] as shown in

Fig. 2. The initial event was set as an RCP trip, and all accidents entered into severe accidents assuming that recirculation of the refueling water storage tank (RWST) is not available.

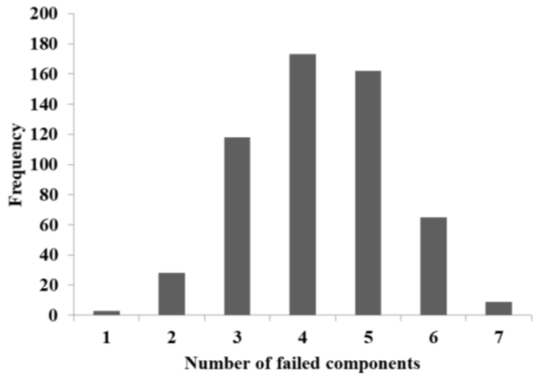

Fig. 1 Frequency of the number of failed components.

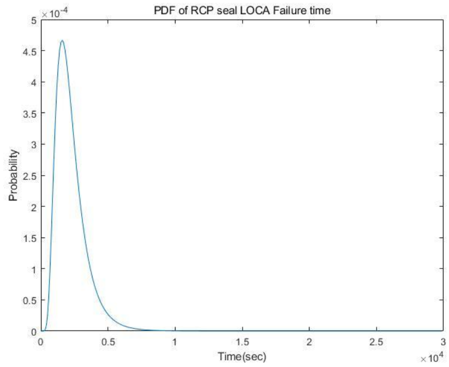

Fig. 2 Log-normal PDF of RCP seal LOCA failure time.

2.3 Artificial Neural Network

The multi-layer perceptron regressor of the scikit-learn tool [7] was applied to predict the reactor vessel failure time. Table II shows the input features for the neural network, which are the failure times of the components, where 72 hours for the failure time indicates the non-failure of the component. In addition, the integer type flags were added in the input features, where 1 and 0 indicate the failure and the non-failure of the component, respectively. The failure times were standardized to remove the scale effects for the neural network fitting. The hyperparameter fitting was performed to find an optimal performance of the neural network using 10 sets of cross-validations. Table III shows the optimized hyperparameter used in this study. The test set was set to 20% of the total data set.

Table II Example input features of neural network

	RCP seal LOCA	HPSI	LPSI	CHP	CSS	HX	MD AFW
Failed time (hr)	1	72	55	72	72	4	72
Failure or not	1	0	1	0	0	1	0

Table III Optimized hyperparameter for multi-layer perceptron regressor

	Activation	Alpha	Hidden layer sizes	Max iteration	Solver
Hyper-parameter	logistic	5e-5	50	100	lbfgs

3. Results and Discussion

After hyperparameter tuning, the performance of the neural network was verified through the test set. The root mean square error (RMSE) is 4.82% (3.5 hr), and the detailed predicted data distribution and trend line are shown in Fig. 3.

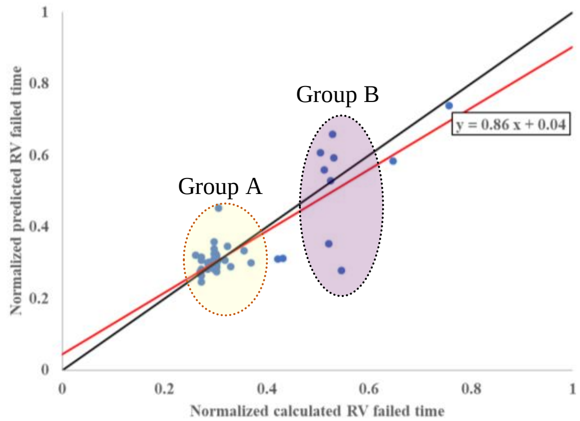

Fig. 3 Predicted vs. calculated RV failed time data with trend line.

The predictions for the early RV fail (group A in Fig. 3) show good performance, while those for the late RV fail (group B in Fig. 3) show bad performance. The reason is that the training data are clustered in the group A rather than group B. As shown in Fig. 4, among 559 datasets, 516 datasets are located in the 0.3-0.4 interval (group A), and there are only 37 datasets in the 0.5-0.6 interval (group B). The training datasets are quite biased to group A. Therefore, more accurate results can be obtained if training datasets are equally distributed. In addition, if the prediction of the neural network can be improved by using the classifier to distinguish between the early and late RV failures.

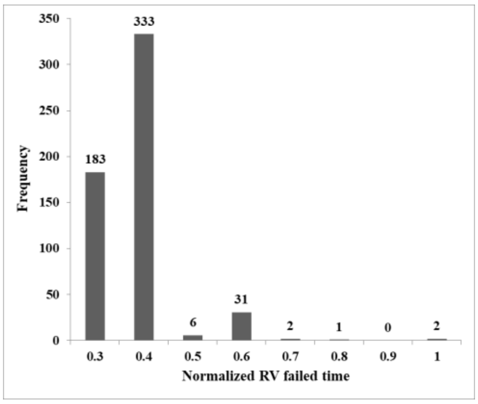

Fig. 4 Distribution of normalized RV failed time results

4. Summary and Further Study

The RV failure time for various component failures in an NPP were predicted using the artificial neural network. The input features were components failure time and integer type flag to distinguish between the failure and the non-failure. The early RV failure results show good prediction, while the late RV failure results are not good due to the biased training datasets. To improve the prediction accuracy, refinement of the training dataset and the classifier to distinguish between the early and late RV failures can be considered in the further study.

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