Transactions of the Korean Nuclear Society Autumn Meeting
Goyang, Korea, October 24-25, 2019

Development of Methodology to Classify Axial Power Shape Using Softmax Regression in Deep Learning

Lee Yongshin*, Jang Chansu, Kim SungDoo,
Sun Jungwon, Nam Younduk, Song Younghan, Choi Kyoungsik, Yun Hangu
KEPCO Nuclear Fuel, 242 Daedeokdaero 989 beon-gil, Daejeon, 34057, Republic of Korea
**Corresponding author: yslee@knfc.co.kr*

1. Introduction

For analysis of Non-LOCA(Non-Loss-Of-Coolant Accident), the safety of nuclear power plants is evaluated throughout sensitivity analysis of initial conditions such as core inlet temperature, RCS(Reactor Coolant System) pressure, reactor coolant flowrate, APS(Axial Power Shape), and so on. In the initial conditions of core inlet temperature, RCS pressure, and reactor coolant flowrate, limiting cases are predicted simply by using maximum and minimum values in the range of LCO(Limiting Conditions for Operation). On the other hand, thousands of sensitivity cases on accident analysis shall be needed by using all of initial APSs which have no obvious tendency. In order to reduce the number of sensitivity analysis, the methodology to classify APSs using Softmax regression in deep learning is developed. Also, uncertainties of DNBR(Departure from Nucleate Boiling Ratio) in the classification group is evaluated in LOF(Loss Of Flow) accidents using the methodology.

2. Methodology

The methodology is to classify new test sets of APS into groups of similar shape using trained deep learning to input APS train sets of label group in Softmax regression. The main flow chart of the methodology is shown as Fig. 1.

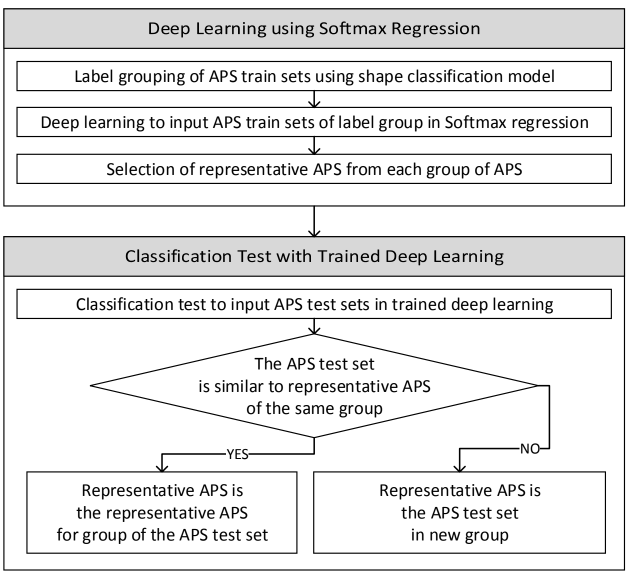

Fig. 1. Main flow chart of methodology to classify APS using Softmax regression in deep learning

2.1 Shape classification model

The shape classification model is developed that APS train sets are labeled according to similarity of shape. In first step, the representative APS and another APS are selected from APS package. Secondly, the similarity between the representative and another APSs are calculated using Eq. (1). These processes are calculated iteratively until classification of APS train sets is finished. The flow chart of shape classification model is shown as Fig. 2.

$$\left|\underline{x}_R - \underline{x}\right|^2 \le \varepsilon \tag{1}$$

where $\underline{x}_R = [x_{R1} \quad x_{R2} \quad \dots \quad x_{RN}]$ is representative APS
$\underline{x} = [x_1 \quad x_2 \quad \dots \quad x_N]$ is another APS
ε is the error for similarity of APS

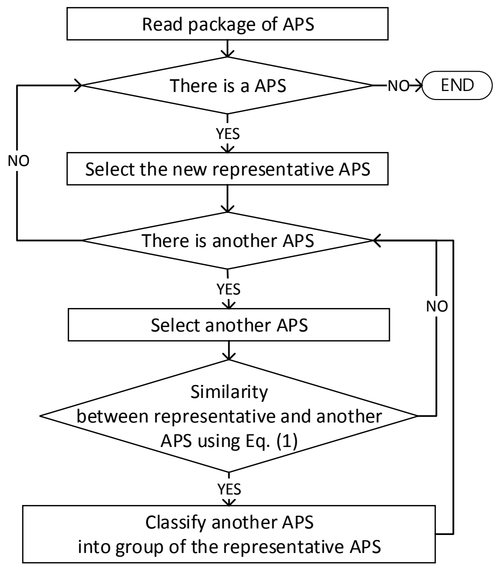

Fig. 2. Flow chart of shape classification model

2.2 Softmax regression of deep learning

Softmax regression[1,2] is the generalization of logistic regression to classify data sets into multiple groups. The applications of Softmax regression are as follows: discriminative face verification[3], facial expression recognition[4], text classification[5], person search from images[6], and so on. Softmax regression consists of Softmax function, cross-entropy function, cost function, and gradient descent.

Applying Softmax function of Eq. (2) normalizes probabilities for output of linear regression. Cross entropy function of Eq. (3) calculates the error between estimated probability values S and real values L for a train set.

$$s_i = s(y_i) = \frac{\exp(y_i)}{\sum_j \exp(y_i)} \quad \text{for } i = 1, 2, 3, \ldots, j \qquad (2)$$

where s_i is probability value of score for i[th] element
y_i is score of i[th] element using linear regression

$$D(S, L) = -\sum_j l_j \log(s_j) \quad \text{for } i = 1, 2, 3, \ldots, j \qquad (3)$$

where s_j is probability value of score for i[th] element
l_j is real value of i[th] element in the train set

Cost function of Eq. (4) calculates mean of the cross entropy function values for all of train sets. In order to minimize the cost function for weighting factors including bias, the cost function is iteratively differentiated by matrix of weighting factors including bias $\underline{\omega}$ until matrix of weight factor including bias converges as shown in gradient descent of Eq. (5).

$$E = \frac{1}{k}\sum_k D(S(\underline{\omega}\underline{x}_k + \underline{b}), L_k) \quad \text{for } n = 1, 2, 3 \ldots, k \qquad (4)$$

where $D_n = D(S_n, L_n)$ is the error between S_n to L_n
$S_n = S(\underline{\omega}\underline{x}_n + \underline{b})$ is probability vector of n[th] train set
L_n is real vector of n[th] train set
k is the number of train sets
$\underline{\omega}$ is matrix of weighting factor
$\underline{b}$ is vector of bias
$\underline{x}_n$ is vector of n[th] train set

$$\underline{\omega}_{t+1} = \underline{\omega}_t - \alpha \frac{\partial E(\underline{\omega}_t)}{\partial \underline{\omega}_t} \qquad (5)$$

where E is cost function
$\underline{\omega}_t$ is matrix of weighting factors including bias for t[th] iteration
α is learning rate

Finally, in order to classify test sets with trained deep learning, the converged matrix of weight factor including bias is applied for trained deep learning of Softmax regression including Softmax function and cross entropy function. As applying the converged matrix of weight factor including bias for Softmax function and cross entropy function, the probability values can be converted into the one-hot encoding as shown in Fig. 3.

Scores		Probabilities		One-hot encoding
2	→	0.7	→	1
1	→	0.2	→	0
0.1	→	0.1	→	0
	Softmax of Eq.(2)		cross entropy of Eq.(3)	

Fig. 3. Example to calculate one-hot encoding using Softmax function and cross-entropy function

3. Results

3.1 Results of APS train sets

As a result of classification for APSs using the shape classification model with the error for similarity of APS 0.5, 2609 of APS train sets are classified into 134 groups as shown in Fig. 4. Most of the similar shapes are biased in some groups of APS package. Especially, group number 51 has 1027 APS train sets and group number 18 has 484 APS train sets. Since all of sensitivity analyses are unnecessary in this biased groups, many sensitivity cases can be reduced by selecting arbitrarily a representative APS in the groups.

In order to analyze differences between maximum and minimum of DNBR, which is DNBR uncertainties, in APS groups, LOF accidents are simulated using 2609 of the APS train sets. Fig. 5 shows the uncertainty of DNBR results in APS groups using shape classification model. Especially, the maximum difference in DNBR uncertainty is 0.021 in group number 86 of APS as shown in Fig. 6. As reducing the error for similarity of APS, the maximum difference in DNBR uncertainty can be reduced. In contrast to decreasing the DNBR uncertainty within groups, the number of sensitivity analyses may increase due to the increase the number of APS groups.

After classifying APSs using shape classification model, the deep learning of Softmax regression with learning rate 0.1 and 15 million iterations is trained. The training is successful to converge in the calculation process for the weighting factor and the training accuracy to compare with the group number of APS train sets labeled by shape classification model is 96.86%.

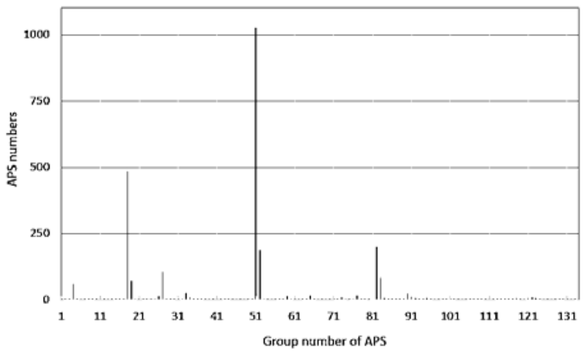

Fig. 4. The number distribution of APS groups using shape classification model

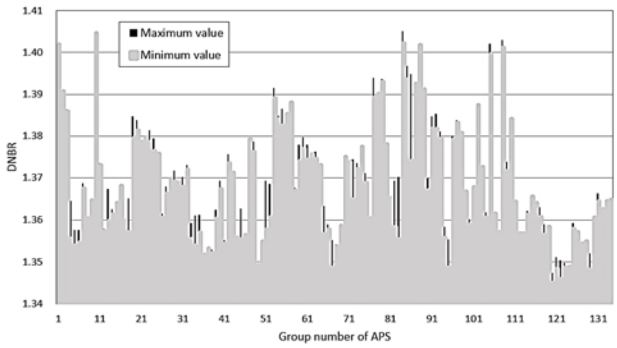

Fig. 5. Uncertainty of DNBR simulated in LOF accident for APS groups using shape classification model

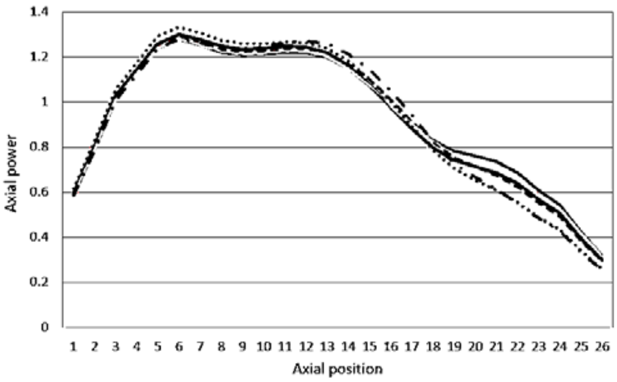

Fig. 6. Axial Power Shapes of group number 86

3.2 Results of APS test sets

3668 APS test sets are tested using the trained deep learning of Softmax regression. The results to classify APS test sets are verified by similarities of shape calculated in Eq. (1) of shape classification model. 3312 of 3668 APS test sets are successful to classify the groups of APS, the accuracy rate is 90.2%.

As a result, the number of the sensitivity analysis in Non-LOCA can be reduced from 3668 APSs to 428 APSs, which consists of 357 representative APSs classified as failed using Softmax regression and 71 representative APSs classified successfully using Softmax regression. As training the deep learning to input more APSs, the number of representative APSs classified as failed using Softmax regression can decrease and the total number of representative APSs can be reduced additionally.

4. Conclusions

The number of sensitivity analysis can be reduced by development of the methodology to classify axial power shape using Softmax regression in deep learning.

To verify suitability of the methodology, the relationship between uncertainties of DNBR and the number of representative APSs needs to be extensively analyzed for various accidents such as SLB(Steam Line Break), LR(Locked Rotor), CEAE(Control Element Assembly Ejection) using more APS train sets according to the errors for similarity of APS. Also, the more APS train sets are needed to increase the accuracy rate for tests of trained deep learning.

REFERENCES

[1] Christopher M. Bishop, Pattern Recognition and Machine Learning, pp.206-210, Springer, 2006.
[2] Dankmar Bhning, Multinomial Logistic Regression Algorithm, Annals of the Institute of Statistical Mathematics, 44(1):197-200, 1992.
[3] Rajeev Ranjan Carlos D. Castillo, Rama Chellappa, L2-constrained Softmax Loss for Discriminative Face Verification, arXiv preprint arXiv:1703.09507, 2017.
[4] Heechul Jung, Sihaeng Lee, Junho Yim, Sunjeong Park, Junmo Kim, Joint Fine-Turing in Deep Neural Networks for Facial Expression Recognition, The IEEE International Conference on Computer Vision(ICCV), pp. 2983-2991, 2015.
[5] Mingyang Jiang, Yanchun Liang, Xiaoyue Feng, Xiaojing Fan, Zhili Pei, Yu Xue, Renchu Guan, Text Classification Based on Deep Belief Network and Softmax Regression, Neural Computing and Application, Issue 1, pp. 61-70, January 2018.
[6] Tong Xiao, Shuang Li, Bochao Wang, Liang Lin, Xiaogang Wang, Joint Detection and Identification Feature Learning for Person Search, The IEEE Conference on Computer Vision and Pattern Recognition(CVPR), pp.3415-3424, 2017.