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Autoencoder optimizations for the signal validation in nuclear power plant accidents

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1. Introduction

Sensor signals in nuclear power plants (NPPs) is an basis of instrumentation and controls (I&C) system, which are performed as a central nervous system of NPPs. I&C system monitor the plant state and actuate the component control and protection system responding to the off-normal situation based on the transffered signals. Sensor signals go through the several analog and digitial system paths, including transmitters, processing units, and cables. Diverse internal and external sources can influence to these signals with fault features.

Validation of signals have to be assurred in any condition of NPP, however, the signal validation in emergency situation can have more significant effect considering the complex and dynamic characteristics from the reactor trip.

In this study, signal validation method in emergency situation in nuclear emegencies was suggested using unsupervised autoencoder model. The autoencoder model reconstruct the multivariate signal with the equivalent inputs. The reconstruction output is analyzed in terms of the residuals from input singals to distinguish the fault signals. To optimized the autoencoder model, feature selections and noble loss function were adopted.

2. Signal reconstruction of sensor fault detection

2.1 On-line monitoring techniques for signal validations in NPPs

Sensor fault detection methods for NPPs have been proposed as an online monitoring techniques to extend sensor recalibration periods and reduce maintenance costs. These methods can be divided into redundant sensor approaches and analytical redundant sensor approaches. For the application of redundant sensor-based approaches in all usable sensors, simpler mathematical or average model can be adopted, however there are economic problems in verifying the signals due to the additional installation of sensors. Analytical redundancy between different sensors uses the relationships between non-redundant sensors to classify sensor states. Analytical technology is preferred because it can be applied without additional redundancy sensors equipments. The analytical redundancy-based online monitoring models, such as auto-associative kernel regression (AAKR), auto-associative neural networks (AANN) were developed for signal validations considering parameter nonlinearities [1]. These approaches showed high performances in normal operation and specific transient cases, however, the model performance were not verified in more complex and dynamic conidtions.

2.2 Unsupervised learning based singal reconstructions

AANN, which is one of the previously applied OLM technique, is based on the neural network-based signal reconstructions. The shape of structure with feature compression and decoding sequence is recently called an autoencoders. Autoencoder generates the compressed feature with input and reconstruct the output with same features with the input. In this sequence, all input signals are concerned with the regression of other signals. For the sensor fault monitoring, reconstructed signals are compared with an input signal, in results, the sensor state is decided with residual analysis as Fig. 1.

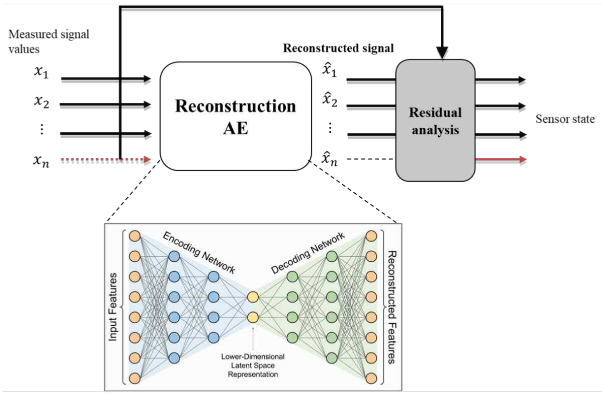

Fig. 1 Autoencoder based signal reconstruction for the sensor fault detection with residual analysis

In our prior research [2], several autoencoder models based on the aritificial neural network (ANN), convolutional neural network (CNN), recurrent neural network (RNN) and stacked ANN are compared to determine desriable autoencoder model for the sensor fault detections. Comparative studies indicates that autoencoder comprising of RNN and ANN models with the min-max normalization has optimal reconstruction performance among the compared models. In spite of the fine performance of the reconstruction, the accuracy of the regression was not enough for the accurate classification of the sensor state. To promote the reconstruction performance, additional consideration in feature selection and loss function adjustments is essential.

3. Autoencoder optimizations using feature selection and loss function

3.1 feature selection for sensor fault detection

Emergency operation procedures (EOPs) are prepared in main control rooms as a guidance for plant operators assuring the optimal responses following the event symptoms. EOPs include the responses at the early reactor trip phase and identifying occurred accidents. These EOP tasks are completely dependent on plant parameters which means the symptoms of the occurred accident. Thus, parameter lists on EOP are optimized parameter sets for situation awareness of emergency situations and response planning. The parameters on the EOP can be regarded as optimized ky feature sets based on the thermal hydraulic experiments and expert knowledge. In this study, we assume these procedure based feature set is physics-informed feature selection.

Feature correlation analysis, which is kind of filter method, is evaluating the feature correlations and results in the feature importance ranks. Each feature was assumed as an independent feature and considering linearity or nonlinearity with a rank of the values, and finally generate highly related feature ranks. In this research, three representative feature correlation measures; Pearson, Spearman, and Kendall correlation coefficient were considered. Below eq. (1)-(3) shows three correlation coefficients. n is the number of observations, C is the number of concordant pairs, and D is the number of discordant pairs.

$$r_{xy} = \frac{n\sum x_i y_i - \sum x_i \sum y_i}{\sqrt{n\sum x_i^2 - (\sum x_i)^2}\sqrt{n\sum y_i^2 - (\sum y_i)^2}} \quad \ldots (1)$$

$$\rho_{xy} = 1 - \frac{6\sum(x_i - y_i)^2}{n(n^2-1)} \quad \ldots (2)$$

$$\tau_{xy} = \frac{C_{xy} - D_{xy}}{C_{xy} + D_{xy}} \quad \ldots (3)$$

In addition to feature selection of the correlation analysis between features, tree-based approaches can be applied considering its many cases and high utility. Extra-tree which is developed tree model from random forest was applied with its advantages in the fast computation and low bias and variance.

3.2 Loss function of the conditional autoencoder

The biggest obstalces to interfere the accurate signal reconstructions in NPP accident data is the dynamic conditions following the various scenarios and various accident conditions such as different break size and location in the same accident type. In conventional autoencoder, all data are trained with unsupervised learning manner.

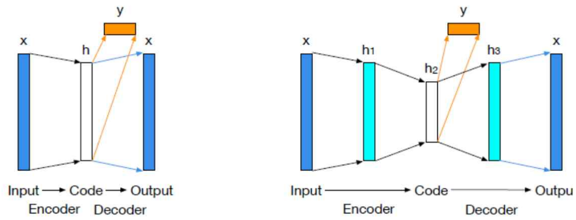

Fig. 2 Conditional autoencoder structure scheme [3]

Conditional autoencoder, as fig 2, was developed to train the autoencoder with contional labels. With the characteristic structure of conditional autoencoder, the signal reconstruction can be trained reflecting the accident labels. The training of each neural node in conditional autoencoder reflects the loss in classification results (conditional label), and reconstruction loss. The loss function for the conditional autoencoder (L) is as below.

$$L(\mathbf{F}) = \frac{1}{t}\sum_{i=1}^{t} L_p(\mathbf{W}_p\mathbf{F}\mathbf{x}_i, \mathbf{y}_{p,i}) + L_r(\mathbf{W}_r\mathbf{F}\mathbf{x}_i, \mathbf{y}_{r,i}) \, . \quad \ldots (4)$$

The classifiction loss (L_p) and reconstruction loss (L_r) are merged and reflected to backpropagation mechanism. The influence rate of each loss can be modulated by adding the weight coefficient (W).

4. Experimental results

To test the signal reconstruction performance with feature selections and newly adopted loss functions, NPP accident database was developed with compact nuclear simulator (CNS). 1-dimensional calculation based CNS can generate accident data with accelerated speed [4]. Among usable plant parameters in CNS, 2083 accident data with 8 accident scenario was generated inclduing 460 features.

4.1 Signal reconstruction with selected features

From the comparative study in prior research, 1-bottle necked ANN and LSTM was selected for the reference model for evaluating reconstruction performance. Based on the thress feature correlation coefficient ranks and Extra tree-based feature selections, the autoencoder training results with target data showed the results as Table 1. The results showed that features from the three correlation-based methods did not converge to the appropriate weights. It can be believed that feature correlation-based feature extraction cannot select features that include the desired features of a trained accident. Linear or non-linear direct correlations are valuable under normal operating conditions for nuclear power plants, but the results suggest that the characteristic relationships need to include accident-distinguishing properties.

Table 1 Autoencoder training results

	Loss	acc
Physics-informed	2.85E-04	0.998
Pearson correlation	1.50E-05	0.354
Spearman correlation	3.12E-05	0.459
Kendall correlation	3.80E-05	0.410
Extra tree	2.27E-04	0.974

Correlation-based feature selection result were excluded because of its failure in convergence. The reconstruction performance of physics-informed feature selection and extra tree importance measure is as Table 2.

Table 2 Reconstruction performance with selected feature selection methods

	Mean error	Maximum error
Physics-informed selection	0.659%	47.57%
Extra-tree nportance measure	0.932%	194.35%

The reconstruction performance in terms of both error index among selected features was evaluated. Reconstructed features with physics-informed selection showed notably remarkable performance than tree-based selection.

4.2 Training results with condition autoencoder

Conditional autoencoder reflects the training results of classification loss and reconstruction loss with the weight coefficient. L_r and L_p depicts the reflection rate of reconstruction and classification. As Table 3, high weight in reconstruction loss overally increase the reconstruction accuracy in noraml data, however, there are threshold that the partial weight of accident label classification loss slightly increase the reconstruction accuracy.

Table 3 Reconstruction accuracy in normal data following the weight coefficient in the conditional autoencoder loss function

L_r	L_p	Reconstruction accuracy (%)
0.1	0.9	95.27
...	...	...
0.5	0.5	96.33
0.6	0.4	96.44
0.7	0.3	96.46
0.75	0.25	96.51
0.8	**0.2**	**96.68**
0.85	0.15	96.63
0.9	0.1	96.28

5. Conclusions

In this study, the signal reconstruction autoencoder for sensor fault detection in nuclear emergencies were optimized with the feature selection methods and newly adopted loss functions for considering the accident label data. Among the feature selection methods, physics-informed (Procedure-based) feature selection method overwhelmed the other model performances. More sophisticated feature selection including wrapper and embedded method need to be compared for more optimized feature set.

As a results of application of conditional autoencoder, we confirmed that high reflection of reconstruction loss overally increase the reconstruction accuracy. However, partial reflection of accident label classification loss improve the reconstruction accuracy. Performed experiment considered only normal signal, thus, experiments with various conditions would show more high applicability of conditional autoencoder model.

6. Acknowledgment

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REFERENCES

[1] Coble, Jamie B., et al. "A review of sensor calibration monitoring for calibration interval extension in nuclear power plants.", 2012.

[2] Choi, Junghun, and Seung Jun Lee. "Comparison of Autoencoder Models for Signal Reconstructions in Nuclear Power Plant Emergencies." PHMAP, 2021.

[3] Le, Lei, Andrew Patterson, and Martha White. "Supervised autoencoders: Improving generalization performance with unsupervised regularizers." Advances in neural information processing systems 31 (2018): 107-117.

[4] Miettinen, Jaakko. "Development and assessment of the SBLOCA code SMABRE." Proceedings of the CSNI Specialists' Meeting on Small Break LOCA Analyses in LWRs, Pisa, Italy. 1985.