Identification of Initial Events in Nuclear Power Plants Using Machine Learning Methods

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1. Introduction

In the event that any event such as a transient going beyond normal operating condition happens in nuclear power plants (NPPs), accurately recognizing and identifying it is essential to establish necessary actions for early mitigating an undesired state under such a circumstance. Especially, initial identification of events, such as a design basis accident (DBA) circumstance in the NPPs, can be one of the critical requisites to prevent from progression to a severe accident. However, correct identification of accident occurrence locations or types may not be easily done on account of monitoring of too many instrumentation signals related to an accident. Therefore, this study is performed to develop models accurately identifying 9 events in initial time after an accident occurrence, and accordingly artificial intelligence (AI) techniques were used to make the models.

Among various machine learning methods based on artificial neural network (ANN) structures as AI techniques, long-short term memory (LSTM) [1] and gated recurrent unit (GRU) [2], which are with the recurrent neural network structure, were utilized in the study. The main reason why these methods were applied is that recurrent neural network structure has an advantage that information in previous steps in its network is relatively well transferred to current and next steps than other methods with typical feedforward network structure (e.g. deep neural network (DNN) or convolutional neural network (CNN) [3]). In addition, since event identification model using the DNN was developed and its result was compared with that of support vector machine (SVM) model in the previous study [4], in an attempt to check performance on various event identification by newly applied methods in the study, the models were developed using the LSTM and GRU.

Thus, identification results for 9 initial events of the LSTM and GRU models are shown in this paper. Furthermore, ongoing work on event identification through clustering using an unsupervised learning method, as another AI technique, is briefly indicated in the paper.

2. Machine Learning Methods Based on Recurrent Neural Network Structure

Recurrent neural network (RNN) [3], basic framework of the LSTM and GRU, can be simply explained as the dynamic neural network with input and output layers, and hidden layer with loop expressed as Fig. 1. That is, a hidden state in a current step is affected by a hidden state from a previous step in the RNN as Eq. (1), and lastly a value to be outputted in the output layer is computed using the hidden state as Eq. (2). Hence, RNN or RNN-based methods are known as effective methods particularly in time-series analysis.
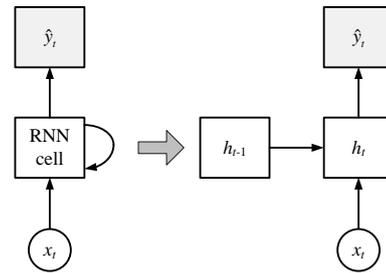
Fig. 1. Simple recurrent neural networks

$$h_t = \phi\left(W_h x_t + U_h h_{t-1} + b_h\right) \tag{1}$$

where W and U are weights, b is bias, and ϕ is an activation function.

$$\hat{y}_t = \phi(W_y h_t + b_y) \tag{2}$$
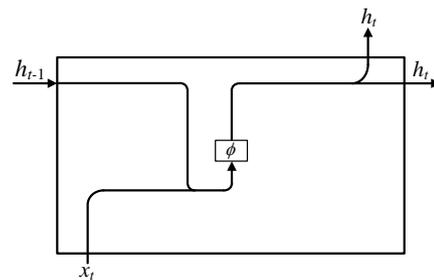
Fig. 2. A hidden cell of RNN

Notwithstanding this characteristic of the RNN, the basic RNN can encounter long term dependency problem, which denotes that the networks can not be effectively learned using the hidden states in the previous steps far from the current step when its hidden layer gets denser. Accordingly, the LSTM and GRU were presented to overcome this problem. These two variations have different revised hidden cells in the hidden layers in the basic RNN framework and each of the specific hidden cells in the LSTM and GRU is a

main factor to solve the aforementioned problem. Fig. 2 indicates a hidden cell of the basic RNN.

2.1 Long-Short Term Memory

A hidden cell of the LSTM is called as "memory cell" and indicated as Fig. 3. The key of the LSTM is cell state in the memory cells as conveyer belt; it continuously transfers information in the current step to the next steps and has function to prevent gradient from vanishing. The LSTM cell in the current step is updated and controlled by three types of gates such as forget, input, and output. Namely, the information in the previous step is selectively propagated to the next cells by removing or adding using these gates.
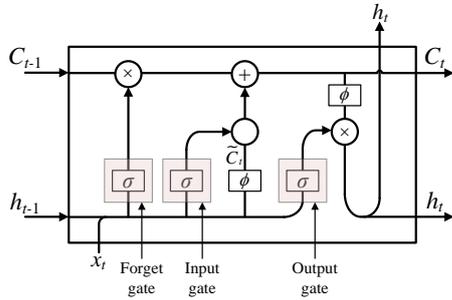
Fig. 3. A memory cell in LSTM

Eqs. (3)-(5) indicate the forget, input, and output gates influential in the cell state in the LSTM cells, respectively. Each gate generally outputs hidden state of the previous step to values between 0 and 1 using sigmoid function to determine how much information is applied to the cell. If an outputted value from the sigmoid function is 1, the information is totally used in the cell. On the contrary, the information fades in case that the value gets closer to 0. The cell states and hidden states in the LSTM are calculated as Eqs. (6) and (7), respectively.

$$f_t = \sigma\left(W_f x_t + U_f h_{t-1} + b_f\right) \tag{3}$$

$$i_t = \sigma\left(W_i x_t + U_i h_{t-1} + b_i\right) \tag{4}$$

$$o_t = \sigma\left(W_o x_t + U_o h_{t-1} + b_o\right) \tag{5}$$

$$C_t = f_t * C_{t-1} + i_t * \widetilde{C}_t \tag{6}$$

$$h_t = o_t * \phi(C_t) \tag{7}$$

where $*$ denotes element-wise product (Hadamard product).

2.2 Gated Recurrent Unit

The GRU, one of the well-known variations of the LSTM, is a method simplifying the LSTM and contains hidden cells in its hidden layers expressed as Fig. 4. The main characteristic of the GRU is that it has less parameters than the LSTM even similar. For instance, only two types of internal gates such as update gate, which is considered as integration of the forget and input gates in the LSTM, and reset gate are in the hidden cells of the GRU, and moreover the cell state and the hidden state are combined as one hidden state.
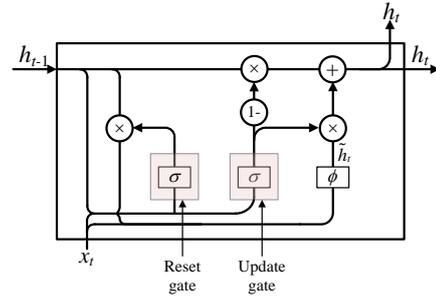
Fig. 4. A hidden cell of GRU

Eqs. (8) and (9) denote the update and reset gates of the GRU. Each gate literally has a role to determine update ratio using the information from the previous and current steps and reset the information from the previous step, respectively. The sigmoid function is generally utilized for two gates in the GRU cells, which is the same as the LSTM cells. The hidden state in the GRU is calculated using an output from the update gate and a candidate in the current step as Eq. (10).

$$u_t = \sigma\left(W_u x_t + U_u h_{t-1} + b_u\right) \tag{8}$$

$$r_t = \sigma\left(W_r x_t + U_r h_{t-1} + b_r\right) \tag{9}$$

$$h_t = (1 - u_t) * h_{t-1} + u_t * \tilde{h}_t \tag{10}$$

where candidate result, $\tilde{h}_t$, is calculated using Eq. (11) as follows:

$$\tilde{h}_t = \phi(W_h h_{t-1} * r_t + U x_t) \tag{11}$$

3. Data of Postulated Accident Situation in NPPs

3.1 Data Acquisition by Simulating Accidents

Identification models of initial events in the NPPs developed using the LSTM and GRU are based on accident symptoms, which is the same as the model established in the previous study [4]. In other words, the

events are identified applying trends of various monitoring variables under several accident circumstances to the AI methods.

As an accident analysis software, modular accident analysis program (MAAP) code [5] was utilized to obtain hypothetical data by simulating 9 accidents postulated according to break locations and sizes, cause of occurrence, and progression circumstances after an accident occurrence with an assumption that safety systems of the NPPs are failed. The simulated data obtained from the code were used to the proposed AI methods. Table I shows accident type considered in the study, data type, and the number of obtained simulation data. The accidents considered in the study are loss of coolant accidents (LOCAs) at hot-leg and cold-leg, steam generator tube rupture (SGTR), main steam line break (MSLB), feedwater line break (FWLB), total loss of feedwater (TLOFW), station blackout (SBO), co-occurrence of MSLB and SGTR, main feedwater pump failure (MFPF).

Table I: Number of applied simulated data

Accident type	Data type		Total
	Learning	Validation	
Hot-leg LOCA	190	10	200
Cold-leg LOCA	190	10	200
SGTR	190	10	200
MSLB	5	2	7
FWLB	5	2	7
TLOFW	2	1	3
SBO	2	1	3
MSLB+SGTR	190	10	200
MFPF	2	1	3

All the obtained data consist of 30 simulated instrumentation signals such as temperature, pressure, and water level from some of the components in the NPP systems, and show numerical values for each simulated signal from the reactor scram to elapsed time to containment failure. Among all the simulated signals, only 13 types of those were applied as inputs to the LSTM and GRU methods.

Each of the simulated signal values according to elapsed time was converted to time-integrated values in a short time interval after the reactor scram using Eq. (12) to train the methods. The integrating time span was considered up to 10 seconds since the proposed models in the study are focused on immediately identifying the events after an accident occurrence.

$$x_j = \int_{t_s}^{t_s + \Delta t} g_j(t)dt, \quad j = 1, 2, \cdots, 13 \tag{12}$$

where $g_j(t)$ is a simulated signal, Δt is an integrating time span, and t_s is reactor scram time.

4. Event Identification Results Using Proposed Models

4.1 Event Identification Results Using Proposed Models

Identification results of the LSTM and GRU models were separated in case of without a measurement error and with several measurement errors, respectively. Since it is considered that measurement errors for the instrumentation signals can occur in the accident circumstances, six types of errors such as -3%, 3%, -5%, 5% specific errors, and random errors between ±3% or ±5% were applied to each simulated signal.

The number of incorrect identification is for all the validation data in Table I in case of without a measurement error, while the number of incorrect identification is for all the obtained 823 data in Table I when measurement errors were applied to the data. Tables II and III show identification results of the LSTM and GRU models, respectively.

Table II: Identification results using LSTM model

Time span	No. of incorrect identification						
	0%	-3%	3%	-5%	5%	Random (±3%)	Random (±5%)
3	1	2	1	3	1	1	1
5	0	2	0	3	3	1	1
7	0	2	0	7	3	0	1
10	0	2	3	6	7	1	4

Table III: Identification results using GRU model

Time span	No. of incorrect identification						
	0%	-3%	3%	-5%	5%	Random (±3%)	Random (±5%)
3	1	1	0	1	1	1	2
5	0	0	0	0	0	0	1
7	0	0	0	6	1	0	1
10	0	0	0	3	3	0	5

Each proposed model has shown the number of 1 incorrect identification result in time span 3 in case that the simulated data without a measurement error were applied. However, several mis-identification results have been shown from two models which were tested using the data with measurement errors. Although each model is naturally affected by the measurement errors, the GRU model in the study can be regarded as slightly better than the LSTM model since the GRU model has shown its higher accuracy in overall cases.

4.2 Comparison Results of Proposed Models with Those of SVM Model

Since several events were relatively well identified by the SVM [6] than another AI method in the previous study [4], performance for 9 event identification of the SVM model was compared with the LSTM and GRU models. The identification result of the SVM model is shown in Table IV. Likewise, the number of incorrect identification is for 47 validation data in case of without a measurement error and the number of incorrect identification for all the 823 simulated data is when measurement errors were applied to the data.

Table IV: Identification results using SVM model

Time span	No. of incorrect identification						
	0%	-3%	3%	-5%	5%	Random ($\pm3\%$)	Random ($\pm5\%$)
3	1	1	1	5	1	1	2
5	0	1	0	4	3	0	1
7	0	0	0	7	4	0	0
10	0	2	4	7	7	0	0

Only 1 incorrect identification result has been shown in time span 3 from the SVM model in case of without a measurement error, which is the same as the proposed LSTM and GRU models. In case of measurement errors considered, however, more incorrect results have been shown from the SVM model especially in case of -3, 3%, -5%, and 5% measurement error data applied than the GRU model. Despite the smaller number of incorrect identification from the SVM model in case of with random errors between $\pm5\%$ considered than the others, it is considered that the GRU model is slightly advanced than the SVM model in this study since higher accuracy has been shown from the GRU model overall.

5. Ongoing Work for Event Identification through Clustering Using Unsupervised Learning Methods

Although the LSTM and GRU networks, as types of supervised learning methods, were used to develop the models quite accurately classifying and identifying the NPP events, it is obvious that additional efforts are necessary to deal with the mis-identification results arise from the proposed models without a doubt. Therefore, an additional work is being performed to identify events through clustering using unsupervised learning methods. The main purpose of ongoing work is that event identification information through clustering organized by features extracted from the un-labeled data is compared with that of the supervised learning methods. That is, it is to supplement availability of the information from the AI methods and to conceptually suggest how to deal with the predicted information to support operators' recognition under the undesired circumstances in the NPPs in the future.

6. Conclusions

Although efficacy of each artificial intelligence (AI) method differs according to its inherent characteristic and domains considered for application, the models developed using long-short term memory (LSTM) and gated recurrent unit (GRU) can be regarded as slightly advanced models than the support vector machine (SVM) model in aspect of identification of 9 initial events in the study since too many incorrect identification results have not been shown especially from the GRU model in every time span when the simulated data with measurement errors were applied. However, the proposed models can be shown as incomplete methods on account of occurrence of mis-identification itself. Therefore, it is needed to deal with the identification results from the AI methods. Currently, additional work to identify the initial events through clustering using unsupervised learning methods is being performed. Once an optimized model using the unsupervised learning methods is established, it is considered that availability of the identification information from the AI methods can be conceptually supplemented.

Acknowledgment

REFERENCES

[1] S. Hochreiter, J. Schmidhuber, Long Short-Term Memory, Neural Computation, Vol.9, pp.1735-1780, 1997.
[2] K. H. Cho, B. V. Merrienboer, C. Gulcehre, D. Bahdanau, F. Bougares, H. Schwenk, Y. Bengio, Learning Phrase Representations Using RNN Encoder-Decoder for Statistical Machine Translation, Proceedings of the 2014 Conference on Empirical Methods in Natural Language Processing(EMNLP 2014), pp.1724-1734, Oct.25-29, 2014, Doha, Qatar.
[3] Y. LeCun, Y. Bengio, G. Hinton, Deep Learning, Nature, Vol.521, pp.436-444, 2015.
[4] Y. D. Koo, J. H. Back, M. G. Na, Identification of Transients of Nuclear Power Plants Using Deep Neural Networks, Proceedings of the Nuclear Plant Instrumentation, Control, and Human-Machine Interface Technologies 2019(NPIC&HMIT 2019), Feb.9-14, 2019, Orlando, FL.
[5] R. Henry et al., "MAAP4: Modular Accident Analysis Program for the LWR Power Plants", User's Manual, Fauske and Associates Inc., 1994-2005.
[6] V. Vapnik, "The Nature of Statistical Learning Theory", Springer, NY, 1995.