Improvement of Machine Learning Model to Predict Sequential Event of Severe Accident Depending on Operator Action

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1. Introduction

Predicting the occurrence time of sequential events resulting from the operation of the mitigation systems in the severe accident can help operators to make appropriate decision to mitigate the accident.

In the previous study [1], we developed a machine learning model to predict sequential event (especially an event of reactor vessel failure) that varies with the operating time of the mitigation systems. We designed the two-step prediction model to predict whether and when the event would occur which is called TOSTO ML (Two Step Target Oriented Machine Learning) model.

In this study, we adopted a new algorithm to improve the performance of the first step of TOSTO model. Instead of Random Forest Classifier using non-time serial data which is used in previous study, we chose Bi-directional LSTM (Long Short-Term Memory) algorithm using time serial data as inputs.

Severe accidents initiated by the Large Break Loss of Coolant Accident (LBLOCA) were simulated by MAAP [2] (Modular Accident Analysis Program) version 5.03 with the failure of the safety injection system of APR1400. In this scenario, it was assumed that the operator restored and activated the mitigation systems after core damage. Since the restoring system and making decision requires certain time, various times for the activation are taken as input.

As a follow-up study of the previous one, the scenarios were the same as before. In this study, however, we treated the time-serial measurement data to predict whether the RV (Reactor Vessel) failure occurs or not. It was confirmed that more accurate predictions could be achieved with the new methods comparing to that of previous study.

2. Methods and Results

2.1 Scenario Configuration and Data Generation

The dataset was generated from the MAAP code with about 3,000 scenarios which had various break sizes, break locations such as the hot legs and the cold legs, and actuating timings of the mitigation systems after the core damage in the LBLOCA-induced-severe accidents.

The SI (Safety Injection) system, the CF (Cavity Flooding) system and the CS (Containment Spray) system were selected as the mitigation systems for the LBLOCA-induced severe accidents based on the Level 2 PSA results.

The overall information of input for MAAP is shown in Table 1. Selected input features based on SAMG monitoring parameter are shown in the table 2.

Table 1: Scenario (MAAP input) Configurations

Variables *		Range **
LOCA	Size (dia.)	[6~16] inch
	Location	Hot/Cold leg
time period to be actuated (from core damage) ***	SIS	[900~14,400] sec
	CFS	[900~14,400] sec
	CSS	[1800~180,000] sec

* All variables are stratified by Latin hyper cube sampling [3].
** The minimum actuation time is selected referring to Human Reliability Analysis.
*** 20% of all cases for each safety system is not functional to describe operation fail.

Table 2: Input Features of Prediction Model

Category	Features	
RCS	Pressure	Injection Flow Rate
	Temperature	RV Water Level
S/G	Collapsed Water Level	
PZR	Pressure	
Containment	Pressure	H2 Concentration
	Temperature	
Cavity	Water Level	
IRWST	H2 Concentration	
Operator Act.	SI/CF/CS Actuation Time	

2.2 Data Preprocessing

In order to use the time-serial data as an input of a deep learning model, different data preprocessing method is required. As the MAAP results have uneven time steps, they must be adjusted in-time uniformly. Here, we interpolated the time step of the data to 1 minute.

Unlike the tree-based model (e.g., random forest), the range of the measurement data needs to be normalized for deep learning. In this study, each data column was divided by the maximum value so that the range is set into [-1, 1].

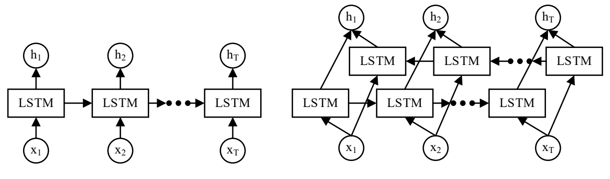
Table 3: Sample for Raw Time-Serial Data from MAAP

	ID	TIME	PPS	PPZ	ZWDC2SG(1)	ZWDC2SG(2)	TCREXITF	PACUM	ZWRWST	WESFDC
0	0	0.000000	1.551848e+07	1.543812e+07	12.405506	12.405506	584.056007	4.302169e+06	3.603909	0.000000
1	0	0.001000	1.551973e+07	1.543811e+07	12.405506	12.405506	584.055976	4.302169e+06	3.603909	0.000000
2	0	1.006664	1.137422e+07	1.469099e+07	12.424536	12.420499	583.907641	4.302172e+06	3.603909	0.000000
3	0	3.761269	1.074905e+07	1.367716e+07	12.398942	12.401380	555.944748	4.302178e+06	3.603909	0.000000
4	0	6.607437	1.006857e+07	1.266656e+07	12.317058	12.319893	561.242177	4.302185e+06	3.603909	0.000000
2766221	2999	264881.066552	8.586871e+05	8.586962e+05	9.632852	9.643619	272.790073	3.017171e+05	3.603909	71.004324
2766222	2999	265181.066552	8.578048e+05	8.578103e+05	9.632586	9.642981	271.859661	3.017171e+05	3.603909	71.038710
2766223	2999	265481.066552	8.569267e+05	8.569337e+05	9.632877	9.643663	270.941793	3.017171e+05	3.603909	71.072309
2766224	2999	265781.066552	8.560115e+05	8.560245e+05	9.632620	9.643032	270.037555	3.017171e+05	3.603909	71.105179
2766225	2999	266051.666552	8.551652e+05	8.551683e+05	9.631986	9.643012	269.233882	3.017171e+05	3.603909	71.134160

2.3 Applied Deep Learning Algorithm

1) Bi-LSTM

A Bidirectional LSTM (biLSTM) is recurrent neural network model which consists of two LSTM models. One takes the input in a forward direction, and the other in a backward. It is used primarily on natural language processing. BiLSTM effectively increase the amount of information available to the network, improving the context available to the algorithm.



(a) Process of unidirectional LSTM (b) Process of bidirectional LSTM

Fig. 1. LSTM and BiLSTM Model [4]

2) Simple Deep Neural Network (DNN)

For comparison, a simple DNN model was developed and trained. The scheme of the model is as follows. It was much easier to make, however, had much more parameters to train than BiLSTM's. Mean square error is used as a loss function while training.

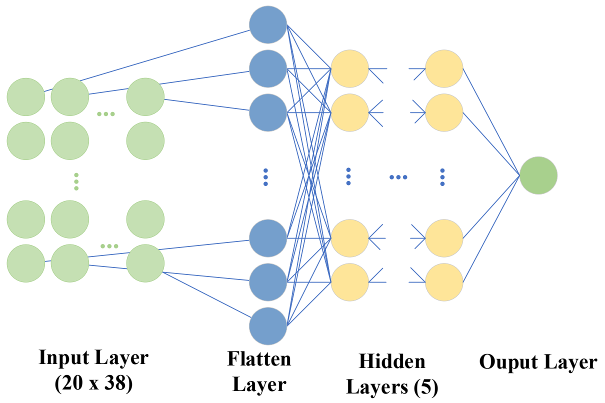


Fig. 2. Simple DNN Model Configurations

2.4 Results

Based on the Random Forest Classifier prediction result with non-time serial data that presents one prediction value for each case, the prediction results of the simple DNN model and BiLSTM model were compared. Since the deep learning prediction model uses time serial data of 20 minutes as an input, prediction can be conducted every minute. Figure 3 shows the results of prediction verifying the accuracy score and F1 score for the 500 cases of test data.

The results show that the performance of DNN model is poorer than that of Random Forest model at the beginning of the accident. But it gets better as time passes and eventually surpasses the RF after about an hour from the accident.

It is also confirmed that the bi-LSTM model shows the best performance from the beginning of the accident and keeps best among three models.

Though the simple DNN model also performed well in prediction, the BiLSTM model showed higher performance even with fewer parameters because BiLSTM model is specialized in time-serial data.

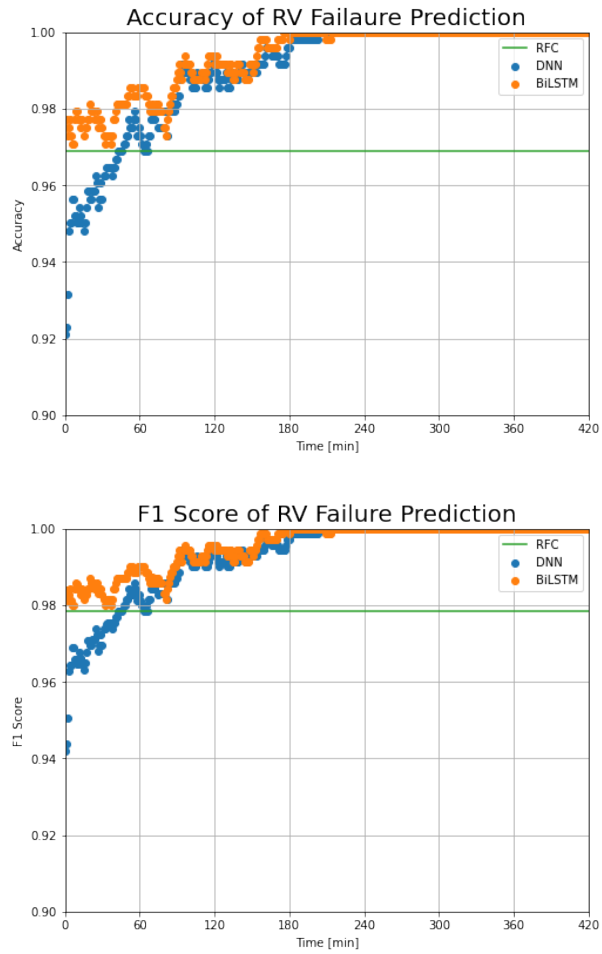


Fig. 3. Results from 3 Types of Models

3. Conclusions

As a follow-up study on the development of a machine learning model for predicting the sequential events after a severe accident, this study was conducted to improve the performance of ML model. A deep learning algorithm was applied to the model that predicts whether RV failure would occur. It is the first part of the two-step model. It is verified that significant performance improvement was made compared to the tree-based model using non-time serial data. In particular, even the simplest neural network model also showed a good performance in some ranges.

In this study, performance improvement was achieved by using Bi-LSTM, a method developed relatively in recent. However, due to the limitations of computational resources, hyperparameters are not fully optimized yet. Therefore, it is expected that the further study on hyperparameter tuning or applications of new algorithms will result in greater performance improvements.

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