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Accelerated prediction of severe accident progression: Sensitivity of deep neural network performance to time resolution

Semin Joo, Seok Ho Song, Yeonha Lee, Jeong Ik Lee[a]*, Sung Joong Kim[b]
[a]*Dept. Nuclear & Quantum Eng., KAIST, 291, Daehak-ro, Yuseong-gu, Daejeon, Republic of Korea*
[b]*Dept. Nuclear Eng., Hanyang University, 222, Wangsimni-ro, Seongdong-gu, Seoul, Republic of Korea*
Corresponding author: jeongiklee@kaist.ac.kr

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1. Introduction

A severe accident refers to a rare event in a nuclear power plant (NPP) where multiple safety systems fail to prevent the core from overheating, leading to the melting of nuclear fuel and potential breaches of the containment system. These types of accidents are highly nonlinear and complex in nature, as they involve multiple safety component failures and intricate processes. The nuclear industry is utilizing advanced modeling techniques, such as MAAP and MELCOR computer codes to model the progression of severe accidents in light water reactors. However, these computer codes usually involve big computational resources and time. With this background, supervised learning has been proposed as a promising method for predicting a nuclear facility's behavior during accident scenarios. Among the various supervised learning techniques, deep neural network (DNN) has an outstanding capability to comprehend the nonlinear characteristics of a given data.

The authors' research team has previously applied DNN to predict the system behavior in a loss-of-component-cooling-water (LOCCW) accident, based on a rolling window forecast method [1]. The rolling window forecast method is a time series forecasting technique where a fixed-size window moves through the historical data one step at a time. At each step, a model is trained on the data within the window, and the forecast is made for the next time point.

Using the surrogate model developed from the previous study, this study is focused on investigating the effect of time resolution on prediction accuracy. If the time resolution of the input data increases (that is, the size of each time step is decreased), it is intuitively expected that the surrogate models predict the system behavior more accurately. However, several studies on the effect of time resolution on the performance of time series forecasting models have produced dissimilar results from this expectation. T. Kim and S. Cho have proposed a CNN-LSTM neural network using the rolling window forecasting method to predict residential energy consumption [2]. They have tested various units for the residential energy data, ranging from minutes to weeks. As a result, the prediction error has increased as the time resolution increases. S. Bu and S. Cho have also tested various supervised learning techniques at various time resolutions to predict residential energy consumption [3]. They have found that the time resolution and prediction error do not necessarily have a linear relationship. These research results raise the question of whether increasing the time resolution of the severe accident data can enhance the prediction performance of the surrogate model. In this light, the main objective of this study is to develop surrogate models for various time resolutions and compare their performance for predicting the progression of LOCCW accident scenarios.

2. Methodology

2.1 Selection of accident scenario

This study focuses on a possible LOCCW accident scenario at OPR1000. In the previous study [1], it has been identified that the product of the frequency of a plant damage state (PDS) and its fraction is the largest at a total LOCCW accident (TLOCCW). In a TLOCCW accident, all seven safety-related components (listed in TABLE I) fail. However, to pinpoint the component most influencing the accident progression, the analysis also considers a subset of TLOCCW accidents. When generating the LOCCW accident scenarios, the safety components' failure times, except for the RCP seal LOCA, were assumed to be uniformly random. Approximately 89.2% of the scenarios featured the RCP seal LOCA occurring at 1 hour.

Table I: List of safety components that fail at TLOCCW

Reactor coolant pump (RCP) seal LOCA
Letdown heat exchanger (HX)
High-pressure injection (HPI) pump
Low-pressure injection (LPI) pump
Containment spray system (CSS) pump
Motor-driven auxiliary feedwater (MDAFW) pump
Charging pump (CHP)

Other than the component failures, accident mitigation strategies are also considered. Three mitigation strategies from the severe accident management guidelines (SAMGs) were selected: SG injection (M1), RCS depressurization (M2), and RCS injection (M3). These strategies are assumed to be activated randomly in time throughout the 72-hour accident.

2.2 Dataset production and post-processing

To simulate the proposed accident scenarios, MAAP 5.03 code was used. The MAAP code predicts the progression of a severe accident scenario for 72 hours, printing out various thermal-hydraulic (TH) variables as a function of time. Among them, ten TH variables that are monitored in the main control room (MCR) were selected as the target variables (see TABLE II). These variables were considered as the minimum required information for the surrogate model to predict the plant state. In summary, a single accident scenario dataset is composed of ten-time series ranging from 0 to 72 hours after the accident initiation. The whole dataset is composed of a random mixture of 11,800 LOCCW accident scenarios and 1,121 TLOCCW accident scenarios.

Table II: List of target TH variables

Primary system pressure
Hot leg temperature
Cold leg temperature
Reactor vessel water level (RV WL)
Steam generator pressure (SG P)
Steam generator water level (SG WL)
Maximum core exit temperature (Max CET)
Containment pressure (CTMT P)
Pressurizer water level (PZR WL)
Pressurizer pressure (PZR P)

Next, the dataset is normalized so that the values fall into the range between zero and one. The scaling process is necessary since each TH variable has different scales and units. As the main objective of this study is to investigate the effect of time resolution, datasets composed of different time resolutions should be prepared. Thus, the normalized MAAP dataset is processed into three different datasets in 60, 30, and 15-minute intervals.

2.3 Structure of the surrogate models

Before the accident dataset is fed into the surrogate models, the DNN models are constructed. In this study, three types of DNN architecture are tested: Convolutional Neural Network (CNN), Long Short-Term Memory (LSTM), and CNN-LSTM. The general structure of the three architectures is similar (see Fig. 1).

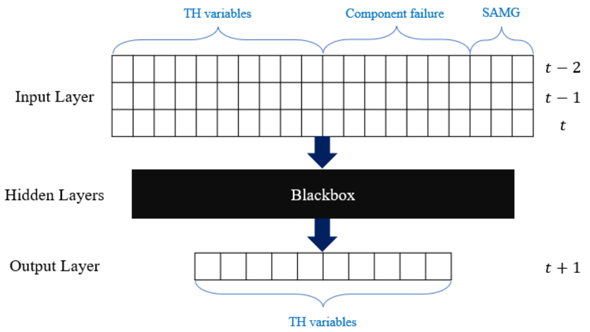


Fig. 1. General structure of the surrogate models

The input layer receives an input dataset composed of 10 TH variables, 7 component failure times, and 3 SAMG activation times at the previous 3-time steps ($t-2,\ t-1,\ t$). The hidden layer is composed of various neural network layers, depending on the type of DNN. Then, the 10 TH variables at the next time step ($t+1$) are displayed through the output layer.

The structure inside the hidden layers of each DNN model, such as the layer type, number of filters/nodes, and activation function, is described in Fig. 2. CNN is specialized in computer vision tasks and feature extraction, while LSTM is effective in time series forecasting and natural language processing. By stacking the CNN and LSTM layers, the model is deepened, thus enabling the model to capture the nonlinear relationship between the input variables.[2]

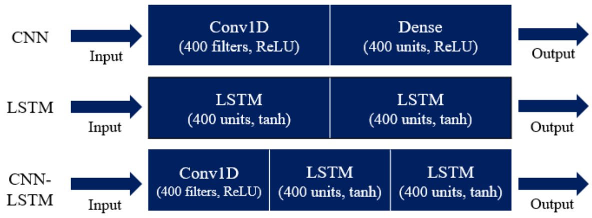


Fig. 2. Structure of the hidden layers inside the surrogate models

2.4 Training and test methods

The 60, 30, and 15-minute datasets are divided into training set (70%), validation set (20%), and test set (10%). The training set is fed into the DNN models to train the models, while the validation set is used to validate the trained model. Next, the performance of the surrogate model is evaluated using the test sets.

The performance of the models is evaluated with two different indexes: mean absolute error (MAE) and Euclidean distance. MAE is an average of the absolute differences between the TH variables predicted by a surrogate model and MAAP code (see Eq. (1)).

$$MAE = \frac{1}{N_{TH}} \sum_{i=1}^{N_{TH}} \left| y_{pred,i} - y_{MAAP,i} \right| \qquad Eq.(1)$$

$$\begin{aligned} &where\ N_{TH} = number\ of\ TH\ variables \\ &y_{pred,i} = TH\ variable\ i\ predicted\ by\ surrogate \\ &y_{MAAP,i} = TH\ variable\ i\ predicted\ by\ MAAP \end{aligned}$$

While MAE describes the mean error in predicting the TH variables at the next time step, the Euclidean distance (ED_i) shows the average regression performance for a specific TH variable i within a scenario (see Eq. (2)).

$$ED_i = \frac{1}{N_{data}} \sum_{t=1}^{N_{data}} \left| y(t)_{pred,i} - y(t)_{MAAP,i} \right| \qquad Eq.(2)$$

$$where\ N_{data} = number\ of\ data\ in\ one\ scenario$$

As three types of DNN models are trained with three different time resolution data, a total of nine surrogate models are developed.

3. Results and Discussion

3.1 Comparison of MAE

First, the next-step prediction error is discussed by comparing the MAE values. The MAE between the test set generated by MAAP code and the predicted data generated by each surrogate model is plotted in Fig. 4. At every time resolution, the CNN-LSTM model had the smallest MAE. Such a result demonstrates the superiority of the CNN-LSTM model in forecasting complex time series data, which has been reported by multiple studies [2, 4, 5].

As the time step is decreased from 60 minutes to 15 minutes, the MAE values decreased at all DNN models. That is, the next-step prediction accuracy has been improved by increasing the time resolution. Also, it should be noted that the amount of error reduction was the largest in the LSTM model, implying that the LSTM model is relatively sensitive to the input data's time resolution. As the time step becomes smaller, the sequential features of the training data become stronger. Since the LSTM network is specialized in capturing the features from sequential data, the LSTM network likely shows good performance at high-time resolution data.

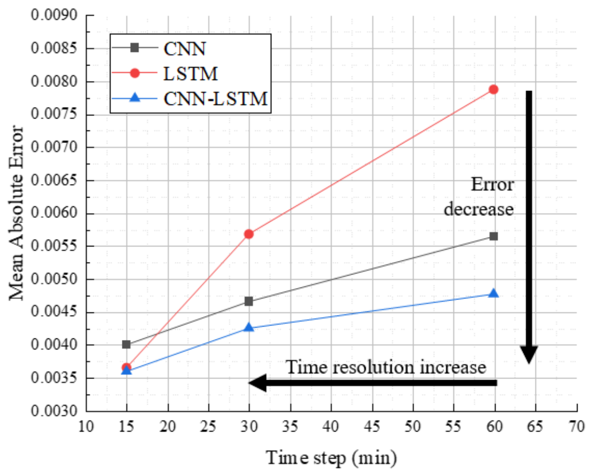


Fig. 4. Comparison of MAE for different DNN structures and different time steps

3.2 Comparison of Euclidean distances

As the purpose of developing the surrogate model is to accurately predict the progression of a LOCCW accident scenario, the regression performance over the whole accident scenario should be evaluated. As discussed in Section 2.4, the Euclidean distance is estimated for each surrogate model to identify which DNN architecture and time resolution can enhance the regression performance. The mean Euclidean distances of each TH variable, which is an average of all ED_i values in the test data, are compared in Fig. 5 for various time resolutions and DNN models.

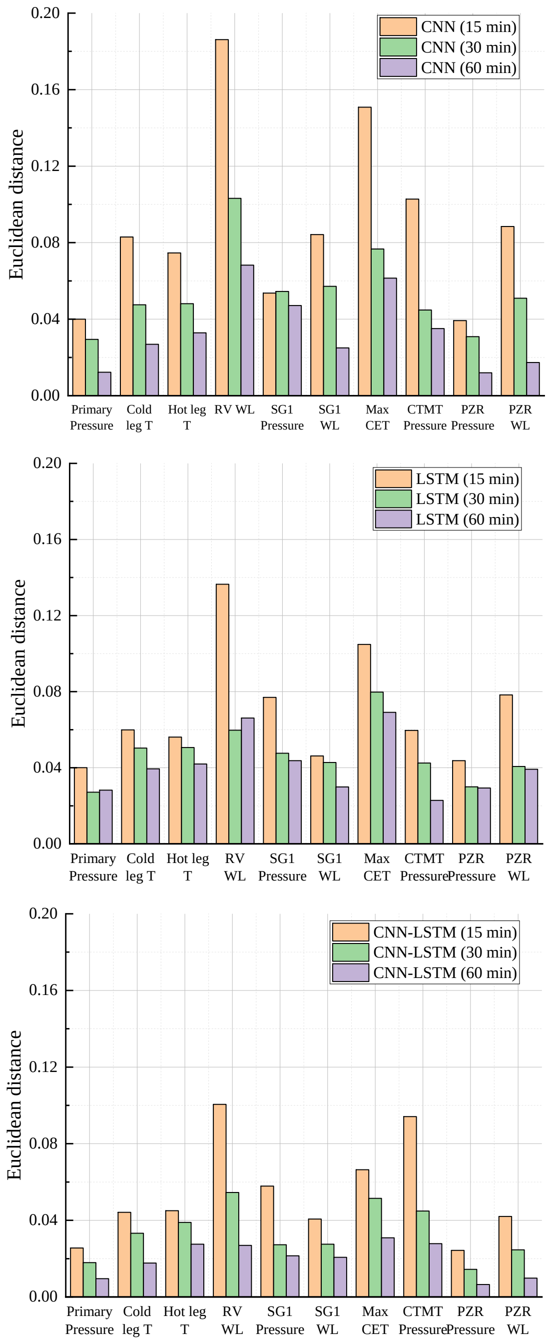


Fig. 5. Mean Euclidean distances of TH variables of CNN, LSTM, and CNN-LSTM models, from top to bottom.

When the time resolution is fixed, the mean Euclidean distances are generally small at CNN-LSTM models. Such a result is consistent with the MAE values discussed in Fig. 4, proving the superiority of the CNN-LSTM model over the CNN or LSTM model.

The mean Euclidean distance is not only affected by the type of DNN model but also by time resolution. It is observed that the mean Euclidean distance increases as the size of the time step decreases, implying that the regression performance over the scenario deteriorates as the time resolution becomes higher. Also, it should be noted that the mean Euclidean distances of RV WL and

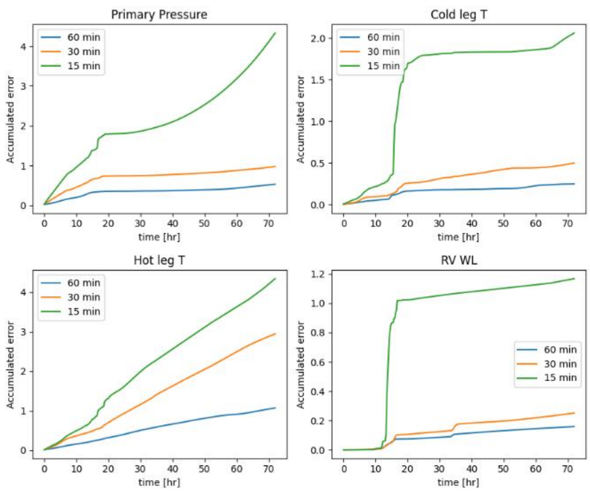
CTMT pressure sharply increase as the time resolution becomes higher.

Such a counter-intuitive result is expected to stem from the accumulation of calculation errors. As the time resolution increases from 60 to 15 minutes, the number of calculations that must be done over a scenario is quadrupled. Although the MAE of each surrogate model has been decreased by increasing the time resolution, the amount of decrement is too small to offset the error accumulated by repeated calculations. To underpin this explanation, the amount of accumulated absolute error between the values predicted by CNN-LSTM models and MAAP code is plotted as a function of time. To perform this calculation, a specific accident scenario has been selected as a test scenario. It is a scenario in which the 15-min model produces the least ED_i values (see Table IV).

Table IV: Component failure times (1-7) and activation times of SAMG strategies (8-10) of the selected accident scenario

	Component/SAMG	Activation time [hr]
1	RCP seal LOCA	1
2	HX	-
3	HPI pump	52
4	LPI pump	-
5	CSS pump	-
6	MDAFW pump	14
7	CHP	63
8	M1	-
9	M2	34
10	M3	-

Based on this scenario, the accumulated calculation error of each TH variable is plotted over 72 hours. It is clearly shown in Fig. 6 that the error is stacked as the accident progresses, and the speed of accumulation is relatively faster at the 15-min model. In contrast, the accumulated error tends to increase slowly and smoothly over time at the 60-min model. Thus, the hypothesis that the repeated calculations have deteriorated the regression performance of high-resolution models has been proven.



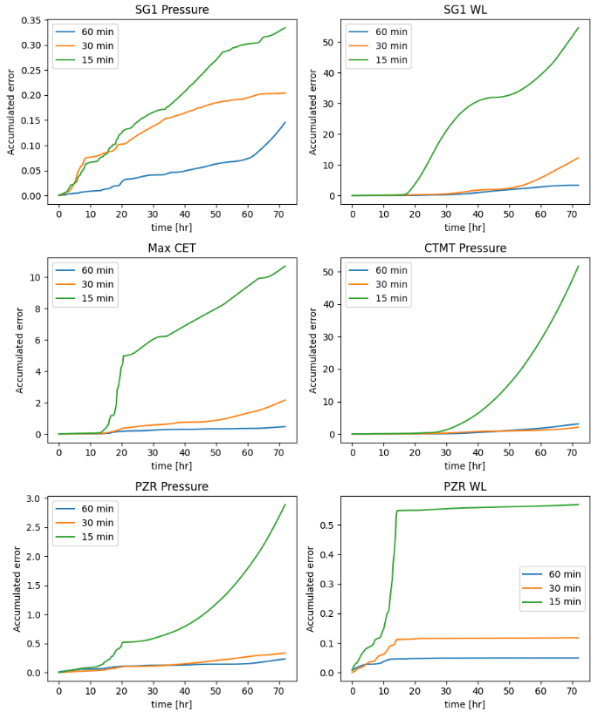


Fig. 6. Comparison of accumulated errors for various time resolutions

4. Conclusions and Further Works

In this study, the effect of time resolution and type of DNN model on the performance for predicting the progression of LOCCW accident scenarios. Using MAAP 5.03 code, LOCCW accident scenarios composed of various component failure times and mitigation strategies were analyzed. Using the MAAP data, surrogate models based on the DNN technique were developed. Three different DNN structures were tested (CNN, LSTM, CNN-LSTM) with three different time resolutions (15, 30, 60 minutes). As a result, CNN-LSTM architecture had the smallest MAE at all time resolutions. When the DNN type is fixed, the MAE decreased as the time resolution increases.

Meanwhile, the regression performance over an accident scenario was evaluated using mean Euclidean distance. Again, the CNN-LSTM model produced relatively small Euclidean distances, proving that it is a promising DNN architecture for time series forecasting. However, the Euclidean distances tended to increase as the time resolution increased. A possible reason behind this is that the frequent calculation at high-resolution models accelerates the stacking of calculation errors. Thus, it is concluded that increasing the time resolution of the surrogate model can reduce the accuracy of the prediction of an accident scenario.

However, there are several limitations to this study. First, the hyperparameters and the structure of the DNN models require further optimization. In this study, all hyperparameters and structures were equally applied at all time resolutions. However, as the time resolution increases, the number of training data increases, thus requiring the size and complexity of the DNN models should be also enlarged. As DNN architectures are dependent on multiple hyperparameters, the optimization process is expected to be tedious.

Although the average prediction accuracy seemed satisfactory, there are several scenarios in which the surrogate models could not predict the peaks or trends on the RV WL, maximum CET. Such deficiencies in the model must be resolved, as the two TH variables are important safety parameters related to core integrity. By optimizing the DNN architectures and carefully analyzing the outlier scenarios, prediction accuracies are expected to be further improved in the near future.

At further studies, the input variables related to the containment integrity will be considered. By adding the parameters related to the containment (such as the concentrations of hydrogen and fission products), the model's prediction accuracy is expected to be enhanced. Also, it is anticipated that the range of accident scenario that the model can predict will be expanded to a containment level.

As the conclusion of this study is that increasing the time resolution can have an adverse effect on the full scenario prediction performance, this leaves us a question of 'what is the optimal time resolution?'. Hence, a method to search for the optimal time resolution and to mitigate the penalties rooting from the stacking of calculation errors will be devised at future works.

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