Accelerated prediction of severe accident progression

Sensitivity of deep neural network performance to time resolution

Semin Joo
Master's Student
Nuclear Power and Propulsion Laboratory (NPNP)
Dept. of Nuclear and Quantum Engineering, KAIST

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INTRODUCTION

Introduction

Motivation

Challenges in severe accident prediction

1) Severe accidents are highly nonlinear and chaotic.
2) DSA & PSA-based methods require large computational resources.
3) Need to develop an alternative method that can incorporate uncertainties with fewer computational resources.

Q Can AI be a tool for the prediction and management of severe accidents?

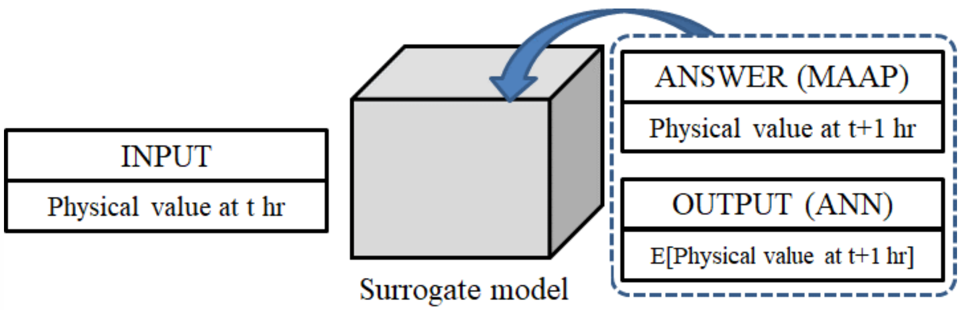

Fig. 1. Development of a data-driven surrogate model
(From 2020 K-CLOUD project "Feasibility study of applying AI algorithms in response to severe accident")

Introduction

Motivation

Sensitivity to time resolution in time series forecasting

- Why time resolution matters
  - In our previous study, the surrogate models were developed based on *hourly* datasets.
  - Predicting the progression of an accident scenario with high time resolution is important.
- Previous studies
  - ***Unclear*** relationship between the time resolution and the prediction performance
  - Ex) Predicting residential energy consumption using supervised learning techniques based on rolling window method

Table 1. Prediction performance of various supervised learning model with time resolution change.

Method	Resolution	MSE	RMSE	MAE	MAPE
Linear Regression	Minutely	0.4046	0.6361	0.4176	74.52
	Hourly	0.4247	0.6517	0.5022	83.74
	Daily	0.2526	0.5026	0.3915	52.69
	Weekly	0.1480	0.3847	0.3199	41.33
LSTM	Minutely	0.7480	0.8649	0.6278	51.45
	Hourly	0.5145	0.7173	0.5260	44.37
	Daily	0.2406	0.4905	0.4125	38.72
	Weekly	0.1049	0.3239	0.2438	35.78
CNN-LSTM	Minutely	**0.3738**	**0.6114**	**0.3493**	**34.84**
	Hourly	**0.3549**	**0.5957**	**0.3317**	**32.83**
	Daily	**0.1037**	**0.3221**	**0.2569**	**31.83**
	Weekly	**0.0952**	**0.3085**	**0.2382**	**31.84**

Time resolution increase

Prediction error increase

*T.-Y. Kim, S.-B.Cho, Predicting residential energy consumption using CNN-LSTM neural networks, Energy 182 (2019).
https://doi.org/10.1016/j.energy.2019.05.230

Q Will this relationship hold the same for severe accident prediction?

Introduction

Research objectives

Main Goals

The main goals of our study are to elucidate the following:

1) Applicability of deep neural network (DNN) to predicting the progression of a severe accident scenario
2) Optimal DNN architecture for time series forecasting
3) Effect of time resolution on the surrogate models' prediction accuracy

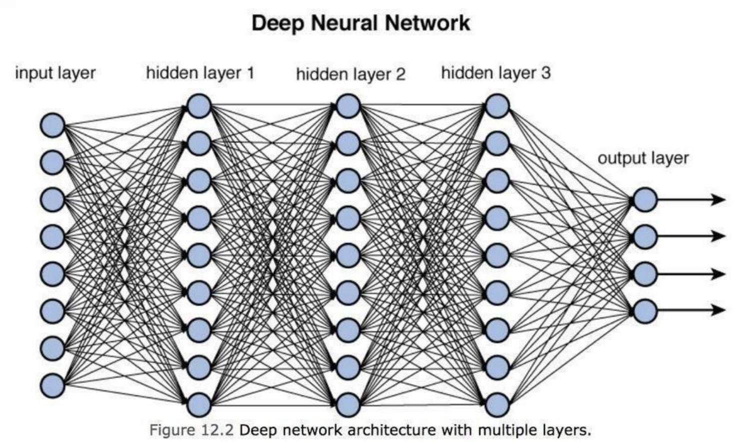

Fig. 2. Deep Neural Network (DNN)

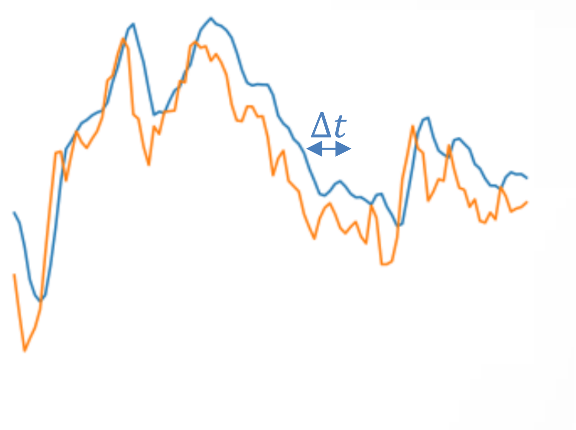

Fig. 3. Time resolution (Δt) of a time series

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METHODOLOGY

Methodology

Selection of Accident Scenario

Accident Scenario

- Reference reactor type: OPR1000
- Total-Loss-of-Component-Cooling-Water (TLOCCW) accident
  - Multiple failures in the safety components lead to reactor core damage
  - High accident frequency (OPR1000 Level 2 PSA report)
- Duration of a single accident scenario: 72 hr (=PSA mission time)

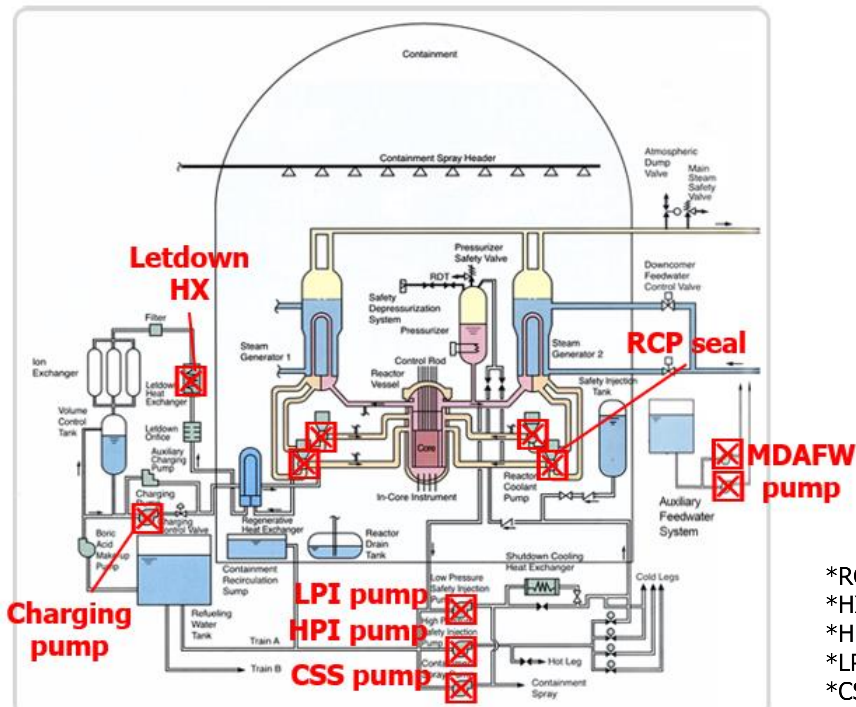


Fig. 4. Locations of component failure at OPR1000 system

Table 2. Types of mitigation strategies (OPR1000 Severe Accident Management Guidelines)

#	Mitigation Strategy
SAMG-01	Steam generator (SG) external injection
SAMG-02	Reactor coolant system (RCS) depressurization
SAMG-03	RCS external injection

*RCP = Reactor Coolant Pump
*HX = Heat Exchanger
*HPI = High-Pressure Injection
*LPI = Low-Pressure Injection
*CSS = Containment Spray System
*MDAFW = Motor-Driven Auxiliary Feedwater
*CHP = Charging Pump

Methodology

Dataset production and post-processing

Dataset production

Component failure/ SAMG activation

Fail at t = 1hr	RCP seal LOCA
Fail or not?	HX
Fail or not?	HPI pump
Fail or not?	LPI pump
Fail or not?	CSS pump
Fail or not?	MDAFW pump
Fail or not?	CHP
Activate or not?	SAMG-01
Activate or not?	SAMG-02
Activate or not?	SAMG-03

→ 12,121 accident scenarios → MAAP 5.03 Code →

TH variables

- Primary system pressure
- Cold leg temperature
- Hot leg temperature
- RV water level
- SG pressure
- SG water level
- Max. core exit temperature
- Containment pressure
- Pressurizer pressure
- Pressurizer water level

*Observable from the MCR and SAMG supervisory variables

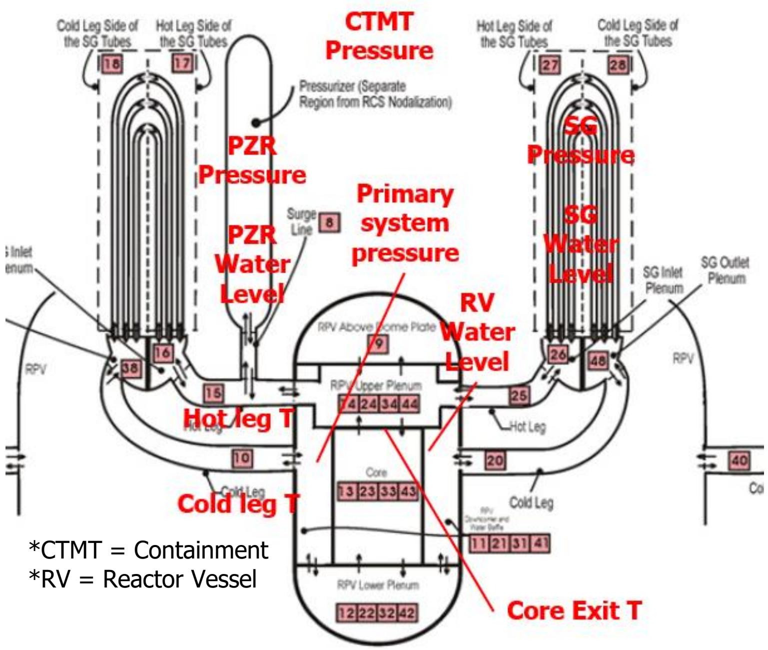


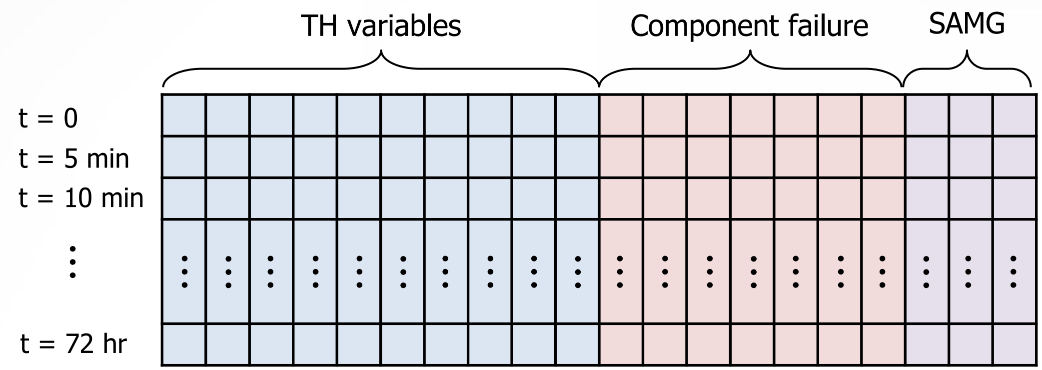
Fig. 5. Location of TH variables at OPR1000

Methodology

Dataset production and post-processing

Dataset post-processing

Original MAAP dataset



x 12,121 scenarios

MinMaxScaler (normalization)

Process the time series datasets into three different time steps

$$\Delta t = 15 \text{ min}$$
$$\Delta t = 30 \text{ min}$$
$$\Delta t = 60 \text{ min}$$

Methodology

Structure of the surrogate models

Structure of the Deep Neural Network (DNN)

- Goal
  - Develop a data-driven model based on a deep neural network architecture
  - quickly predict the important TH variables of a NPP during a accident scenario
- Advantage of DNN
  - Excellent interpretability on non-linear relationships between the input variables
- Method
  - Train the DNN model using the accident data produced by MAAP code

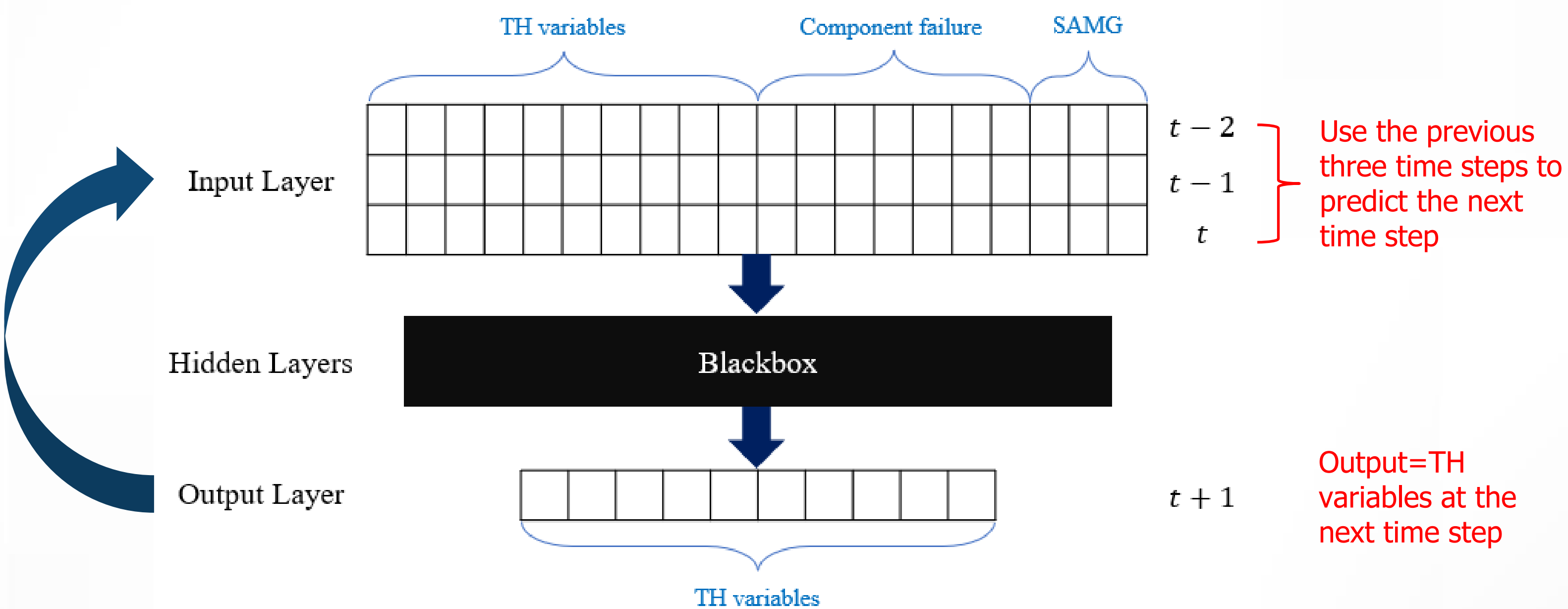


Fig. 6. Structure of the DNN models

Methodology

Structure of the surrogate models

Structure inside the hidden layers

1. Convolutional Neural Network (CNN) — Image processing, feature extraction
2. Long-term Short Memory (LSTM) — Time series forecasting, natural language processing
3. Combination of CNN and LSTM (CNN-LSTM)

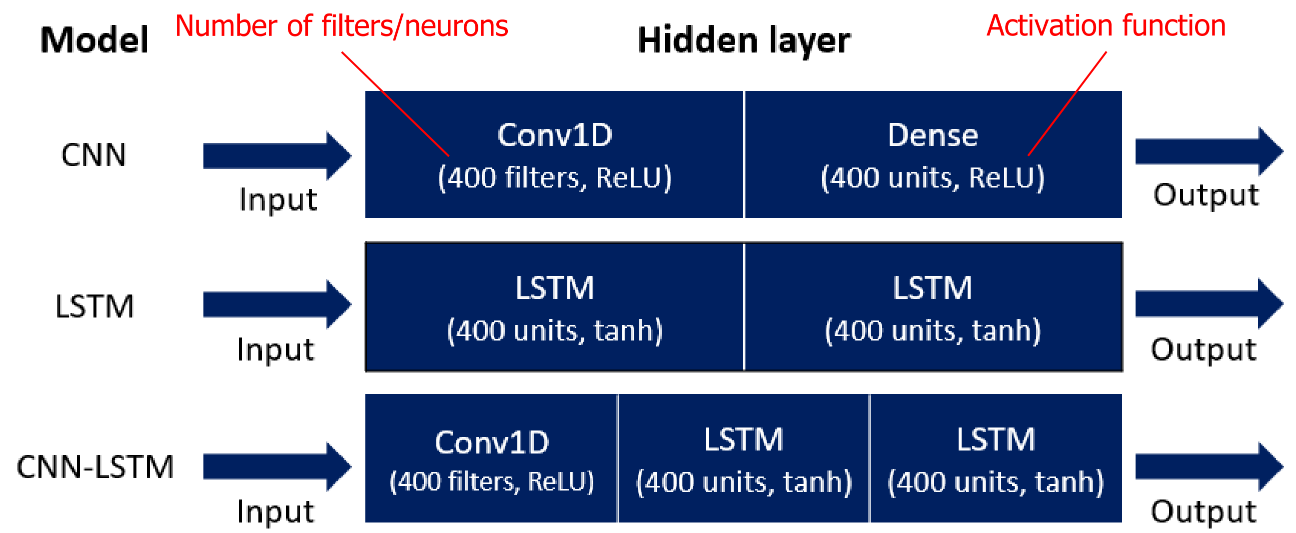


Fig. 7. Structure of the hidden layers inside the DNN models

Methodology

Training and test methods

Training method

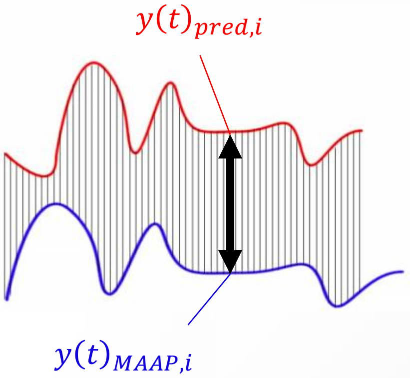
- Hold-out validation
  - Divide the datasets into (training set) : (validation set) : (test set) = 7:2:1
- Early stopping method - When to terminate the training process?
  - If the validation set's mean squared error is not improving for **5 epochs**
- Machine learning library: Python tensorflow, keras (ver. 2.12.0)

Test method

Q) Which metrics/measures would be suitable for comprehensively evaluating our models?

Table 3. Model performance indicators

Mean Absolute Error (MAE)	Euclidean Distance (ED)
How well the model predicts the TH variables at the next time step	Full-scenario prediction performance
$$MAE = \frac{1}{N_{TH}} \sum_{i=1}^{N_{TH}} \left\| y_{pred,i} - y_{MAAP,i} \right\|$$ N_{TH} = number of TH variables $y_{pred,i}$ = TH variable i predicted by surrogate $y_{MAAP,i}$ = TH variable i predicted by MAAP	$$ED_i = \frac{1}{N_{data}} \sum_{t=1}^{N_{data}} \left\| y(t)_{pred,i} - y(t)_{MAAP,i} \right\|$$ $N_{data} = number\ of\ data\ in\ one\ scenario$



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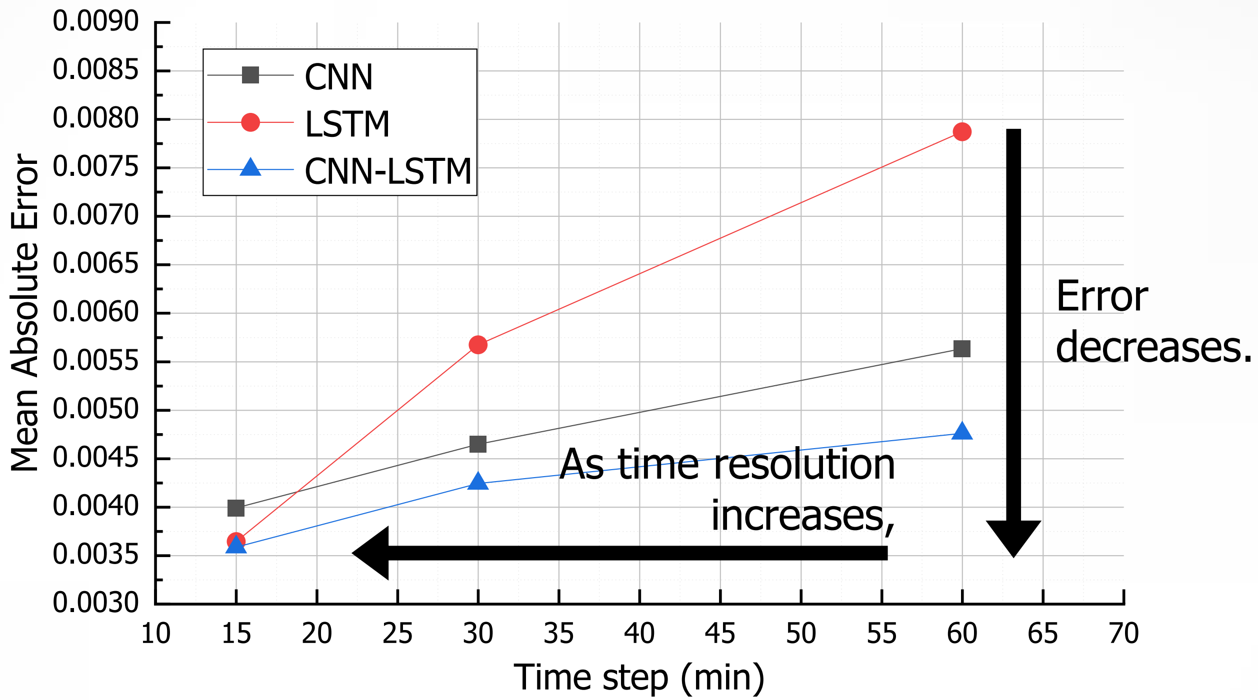
RESULTS AND DISCUSSION

Results and Discussion

Comparison of MAE

MAE comparison *- three time steps, three DNN architectures*

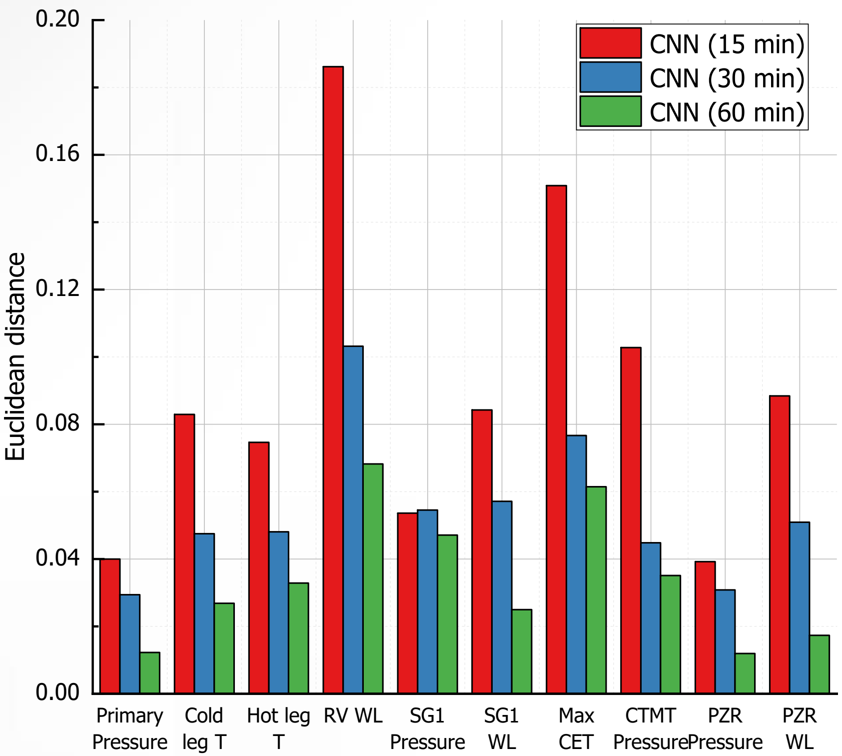


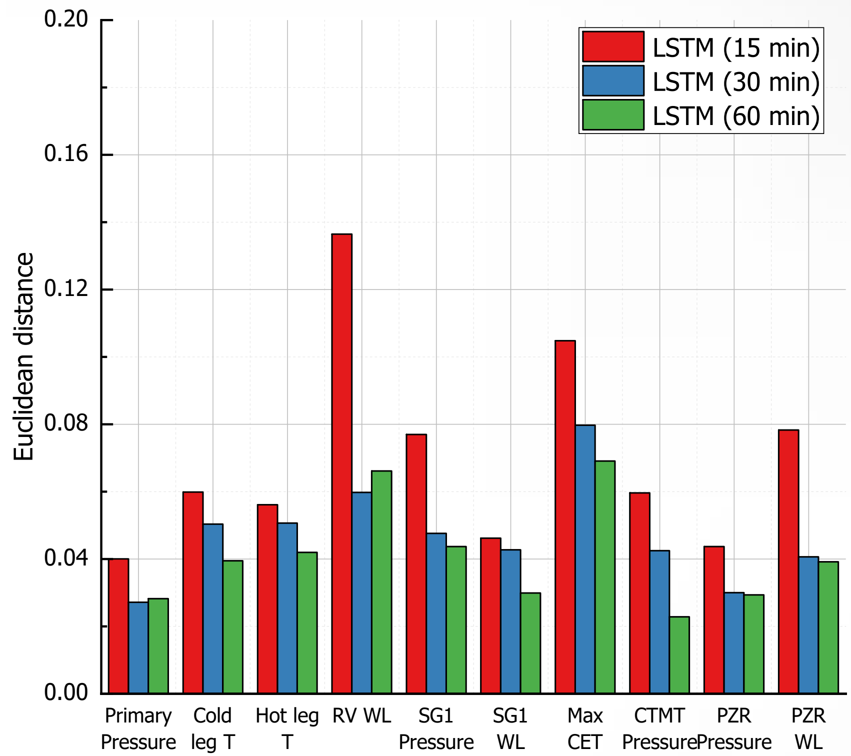
1. As time resolution increases (smaller Δt), MAE decreases.
2. CNN-LSTM model has the smallest MAE.
3. LSTM model's performance is relatively sensitive to the change in Δt.

Results and Discussion

Comparison of Euclidean distance

Euclidean distance comparison *– CNN, LSTM models*

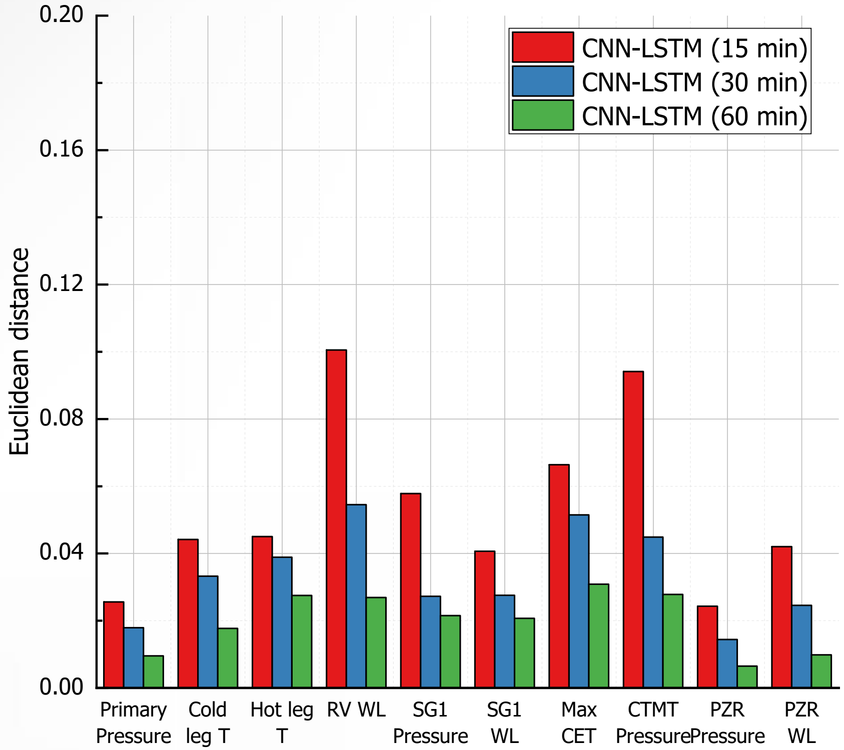




Results and Discussion

Comparison of Euclidean distance

Euclidean distance comparison *– CNN-LSTM model*



General Observations

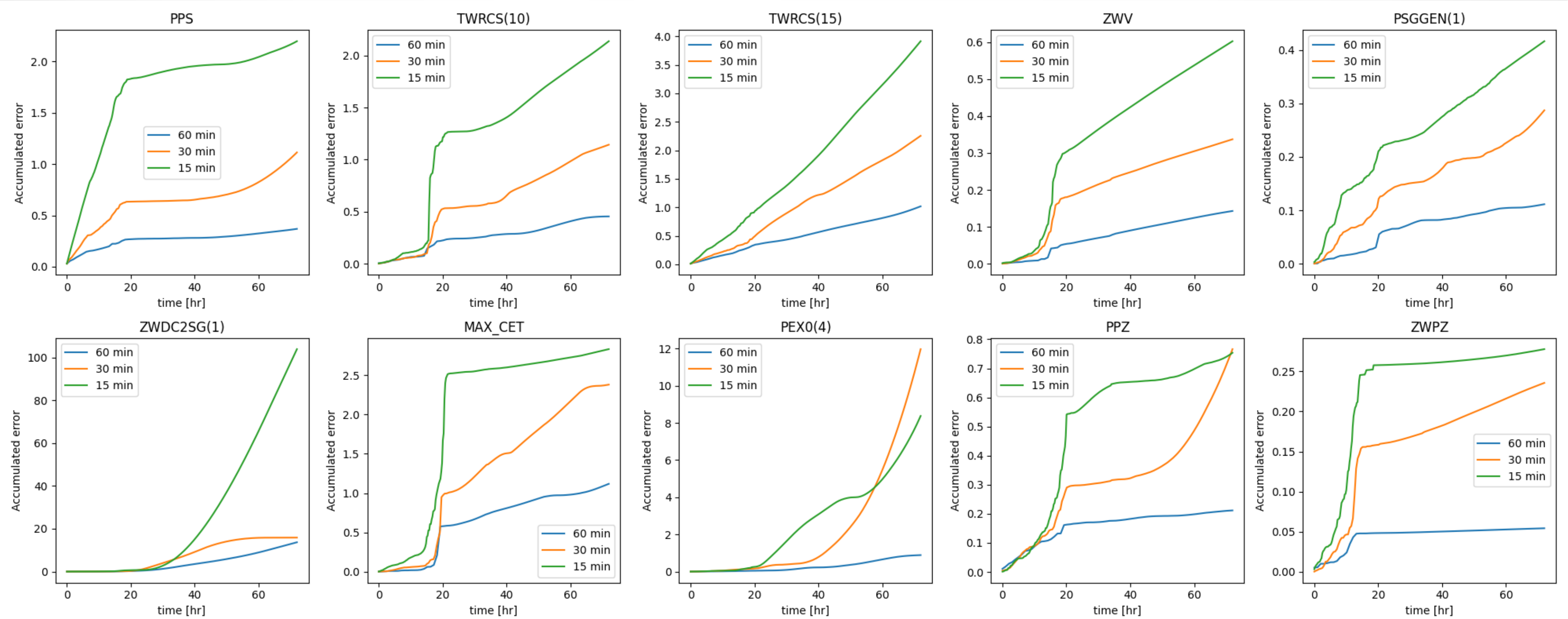
1. As time resolution increases (smaller Δt), Euclidean distances increase.
2. Generally, CNN-LSTM model has the smallest Euclidean distances.
3. Reactor vessel water level and containment pressure are relatively sensitive to Δt.

Results and Discussion

Accumulation of calculation error

Component/SAMG	time [hr]
RCP seal LOCA	1
HX	-
HPI pump	52
LPI pump	-
CSS pump	-
MDAFW pump	14
CHP	63
SAMG-01	-
SAMG-02	34
SAMG-03	-

Accumulation of error - *CNN-LSTM model at a specific accident scenario*



- As the time resolution increases, the speed of error accumulation becomes faster.
- Rolling window forecasting method → **Repeated calculations at high-resolution models** → large deviations from the MAAP data as time passes.

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CONCLUSIONS

Conclusions

Summary

1 **Search for the best DNN architecture**

- Comparison of CNN, LSTM, CNN-LSTM architectures
- *CNN-LSTM model had both the smallest MAE and Euclidean distances*.

2 **Effect of time resolution on the regression performance**

- The regression performance of a model was evaluated by mean absolute error (MAE).
- At all models, *MAE decreased as the time resolution was enhanced to 15 min*.
- The amount of error reduction was the largest at the LSTM model.

3 **Effect of time resolution on the full-scenario prediction performance**

- The full-scenario prediction performance was evaluated by the Euclidean distances between the predicted values and the MAAP simulation results.
- *The Euclidean distances increased as the time resolution was enhanced to 15 min. at all models.*

→ Reason: *error accumulated by repeated calculations* at high-resolution models

Conclusions

Limitations and Further Works

1 **Hyperparameter optimization**

- Current models share the same hyperparameters (e.g., number of nodes, batch size, learning rate, etc.)
- Optimize the hyperparameters for different time resolutions (Usually, the size of the model should be increased with increasing training dataset).

2 **Add input variables related to the containment integrity**

- To expand the model's prediction scope up to the containment level
- To increase the prediction accuracy, more input variables may be needed.

Ex) hydrogen concentration, fission product concentration

3 **Search for the optimal time resolution**

- The conclusion of this study is that increasing the time resolution can have an adverse effect on the full-scenario prediction performance.
- Then, what would be *the optimal time resolution*?
- Search for methods to *mitigate the penalties rooting from the stacking of calculation errors*.

Q&A