Utilizing Artificial Neural Networks to Forecast Remaining Time to Reactor Pressure Vessel Failure during Severe Accident

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Introduction

✓ Nuclear Safety Protocols

Safety and reliability in nuclear power plants are ensured through distinct protocols for different incidents. Design basis accidents and severe accidents are managed using Emergency Operating Procedures (EOP) and Severe Accident Management Guidelines (SAMG) respectively.

✓ SAMG Goals

SAMG addresses Beyond-Design-Basis Accidents (BDA) where the core is severely damaged. SAMG aims to stabilize the damaged core, maintain containment, and minimize fission product release from the core, emphasizing containment and safety in extreme scenarios.

✓ Complexity of Severe Accidents

Severe accidents pose challenges due to the difficulty in establishing connections between phenomena and causes. The outcome of these accidents is highly variable and dependent on specific events, making prediction and mitigation complex.

✓ RPV Failure Prediction

The failure of the reactor pressure vessel (RPV) is critical, as it breaches a key safety barrier, allowing radioactive material release. Predicting RPV failure time based on available accident information is crucial. The study uses artificial neural networks, including Convolution Neural Network (CNN), Long Short-Term Memory (LSTM), and CNN-LSTM, to predict RPV failure time using MAAP simulation data, contributing significantly to nuclear power plant safety.

Methodology

✓ Objective

The study aims to assess the feasibility of using artificial neural networks to predict Reactor Pressure Vessel (RPV) failure time in the context of the Total Loss of Component Cooling Water (TLOCCW) accident scenario.

✓ Dataset Generation

A dataset of 432 accident scenarios is generated using MAAP simulation data, focusing on failures of specific components (RCP seal LOCA and HPI pump) within a bounded timeframe of 72 hours. Six parameters (Table 1), including four pressure variables and temperatures of hot and cold legs, are chosen as inputs for the neural network.

Table 1 Input Parameter for RPV failure Time Prediction

Input Parameters for ANN
Primary Pressure*
Ex-vessel Pressure
Pressurizer Pressure
Steam generator Pressure
Hot leg Temperature
Cod leg Temperature

***Primary Pressure is an average pressure of the reactor upper plenum and the reactor dome in MAAP code**

✓ Neural Network Architectures

The study investigates three neural network architectures – CNN, LSTM, and CNN-LSTM – each with two concealed layers. Input parameters spanning three discrete time steps (30 minutes each) are used to forecast the remaining time until RPV failure (Figure 1).

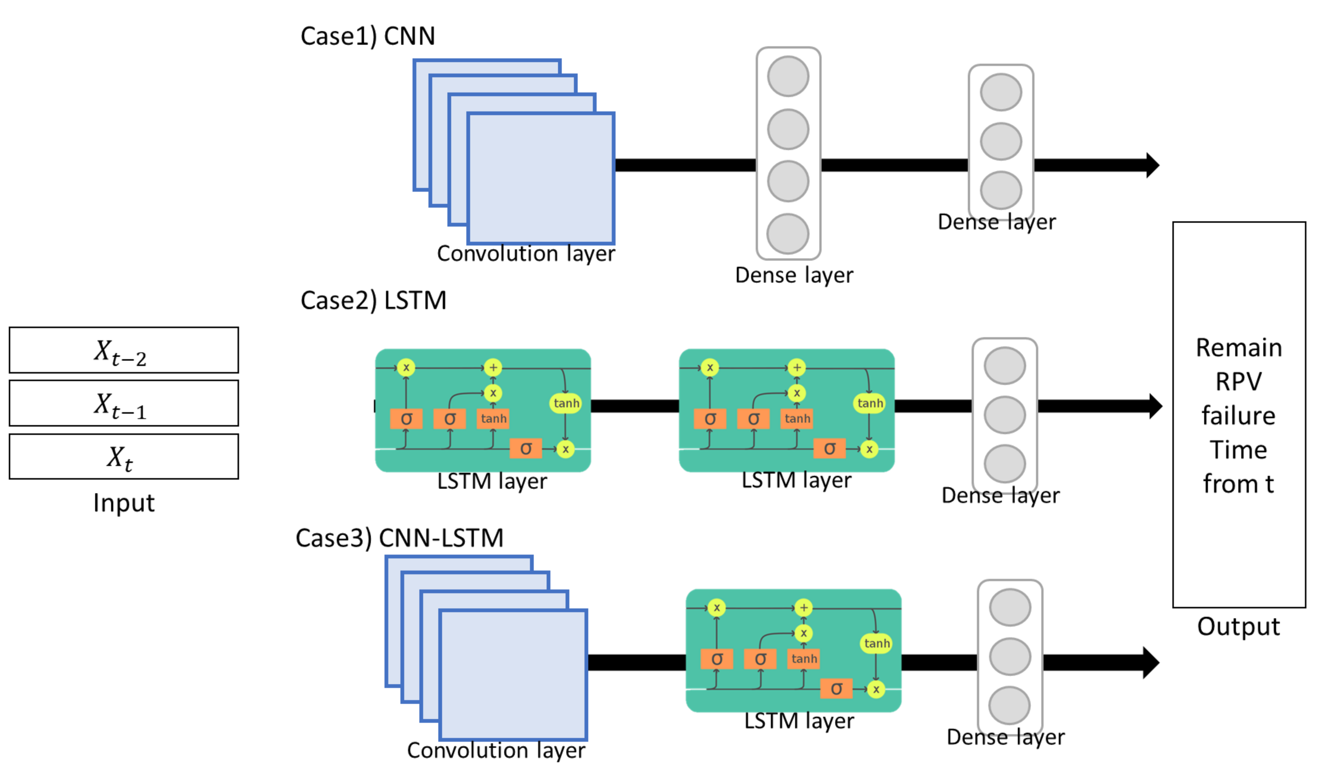

Figure 1 Concept of RPV Failure Prediction Model

✓ Training and Evaluation

The dataset is partitioned into training (80%), test (10%), and validation (10%) sets. Mean squared error is employed as the loss criterion during training. The validation set helps prevent overfitting, and the training process stops when the validation loss reaches its minimal value and remains stable for 100 subsequent training epochs.

Results

✓ Hybrid Model Precision

The hybrid CNN-LSTM model demonstrates the highest precision, with minimal disparity in root mean square error (RMSE) values between training and test sets, indicating a successful and comprehensive model.

✓ Difference Distribution

Figure 2 displays the difference distribution between predicted values and actual MAAP data in the test set, showing a lower standard deviation corresponding to the order of RMSE values in Table 2**.**

Table 2 Root Mean Squared Error of Each model

	CNN	LSTM	CNN-LSTM
Training Set	1.13.E-02	1.02.E-02	9.10.E-03
Validation Set	1.11.E-02	1.08.E-02	9.10.E-03
Test Set	1.04.E-02	1.11.E-02	8.80.E-03

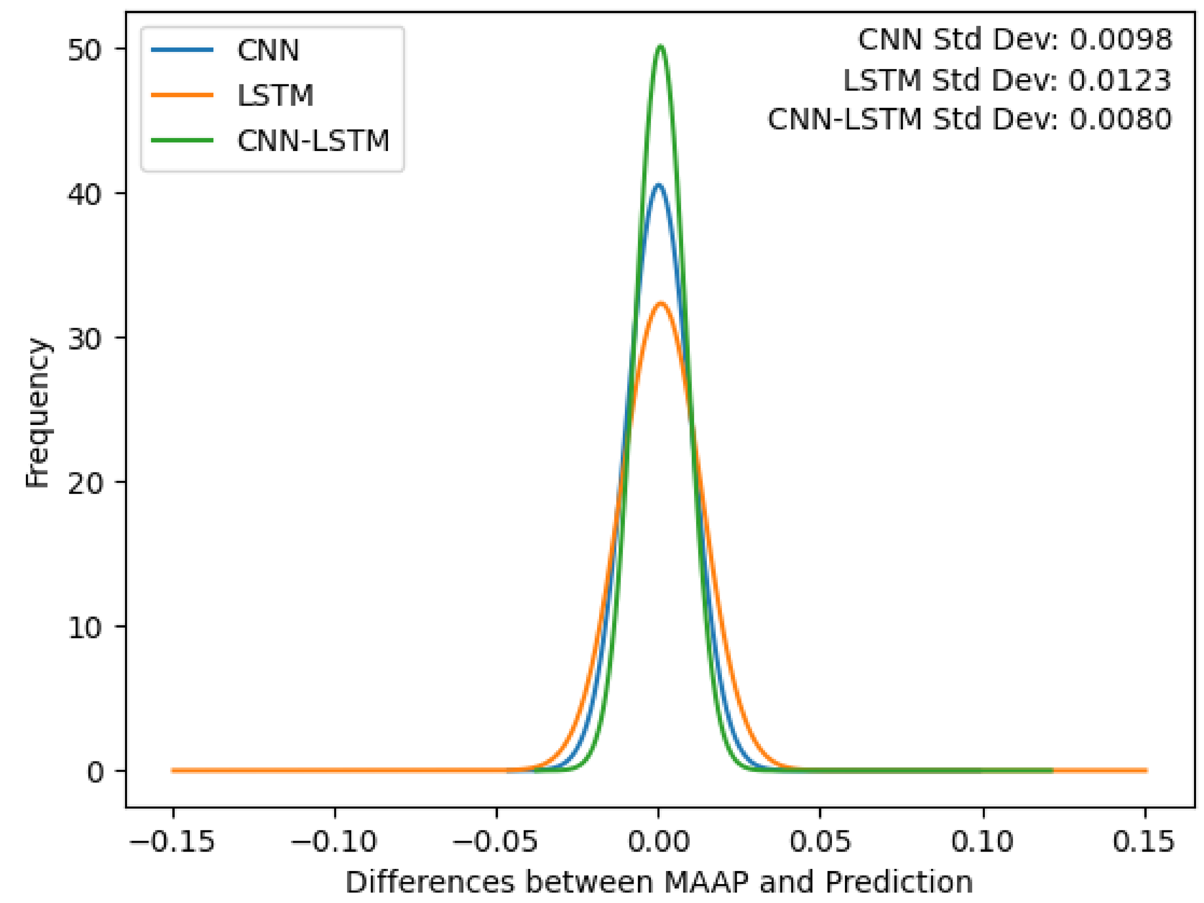

Figure 2 Distribution of Predicted Value of Test set

✓ Early Stage Prediction Accuracy

Predicting Reactor Pressure Vessel (RPV) failure using initial accident data leads to superior accuracy compared to utilizing information from later stages. The dataset's characteristics contribute to this, as the early phase exhibits a consistent pattern before specific failures (RCP seal LOCA and HPI failure) occur, enabling better correlation between input and output data and enhancing the model's predictability

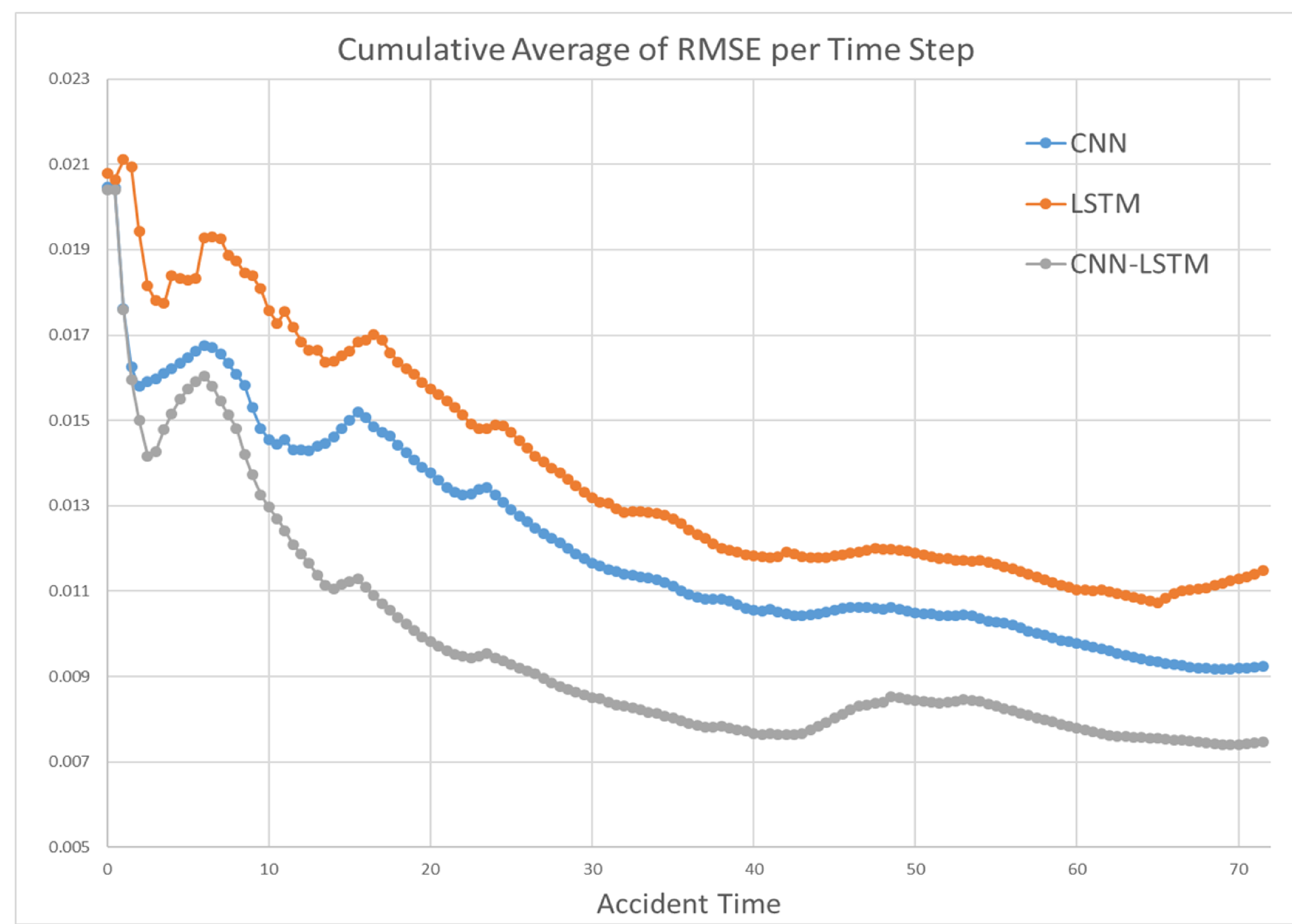

Figure 3 Cumulative RMSE through Accident Progress

Summary & Further Works

1) The study successfully predicts **Reactor Pressure Vessel (RPV) failure time with high accuracy** using data from **TLOCCW accident scenarios**.
2) Among CNN, LSTM, and CNN-LSTM models, the **CNN-LSTM hybrid model** performs the best in RPV failure time prediction.
3) The models are based on **uncomplicated TLOCCW scenarios**, necessitating extension to **more complex scenarios involving various component failures** like LPI, HX, CSS, and MDAFW pumps.
4) The models were trained using data where RPV failure time was known, highlighting the need for future research to explore the models' performance **when RPV failure data is not included in the training dataset**.