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

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1. Introduction

In the ever-evolving landscape of nuclear technology, the paramount objective remains the assurance of safety and reliability within nuclear power plants. To achieve these aims, incidents within these plants are categorized into design basis accidents and severe accidents, each addressed by distinct protocols: Emergency Operating Procedures (EOP) and Severe Accident Management Guidelines (SAMG).

While the EOP is applicable when the core is largely intact and the situation is controllable, the SMAG is applicable when the core overheats, core/fuel damage occurs, a large release of fission products from the fuel occurs, or fission product boundary generation is threatened or failed [1]. Additionally, the SAMG is intended to address Beyond-Design-Basis Accidents (BDA) where the core is severely damaged or has the potential to be damaged. The goals of SAMG are to stabilize the damaged core, maintain containment, and minimize fission product release from the core [2].

Especially for severe accidents, where the impact and damage are greater, various safety measures and technologies are needed. A major characteristic of severe accidents is that it is difficult to find a connection between phenomena and causes [3], and the direction of the accident varies greatly depending on the presence or absence of certain events [4].

Among the events that can occur during the progression of a severe accident, the failure of the reactor pressure vessel (RPV) is of high importance since it is the failure of a key safety barrier that prevents the release of radioactive material to the environment. With RPV vessel failure, the purpose of the accident mitigation strategy shifts from protecting the reactor cooling system to protecting the containment. Therefore, predicting the time of RPV vessel failure based on information available in the accident condition can make a significant contribution to the safety of nuclear power plants.

In this study, a preliminary study was conducted to predict RPV failure time using artificial neural networks. A study was conducted to predict the remaining time until RPV failure occurs using the MAAP simulation data of Total Loss of Component Cooling Water (TLOCCW). The prediction performance of RPV failure time is evaluated for three neural networks and they are compared to each other: Convolution Neural Network (CNN), Long Short-Term Memory (LSTM), and CNN-LSTM.

2. Methods

This study serves as a preliminary study aimed at assessing the viability of utilizing an artificial neural network to predict the time of Reactor Pressure Vessel (RPV) failure. The assessment of the artificial neural network's performance is conducted using a relatively straightforward dataset. Within the context of the TLOCCW accident scenario, the evaluation is focused solely on the failures of two specific components: the RCP (Reactor Coolant Pump) seal LOCA and the High-Pressure Injection (HPI) pump. To emulate the RPV failure, all SAMG mitigations are deliberately disabled.

Given that the RPV failure predominantly transpires between 57 and 67 hours for most scenarios, the simulation time is set to 72 hours. By restricting the occurrence of RCP seal LOCA within the initial 30 minutes, one hour, and an hour and a half of the event, following lognormal distribution from initiation event [5] while limiting the timeframe for HPI failure to 0 to 71.5 hours in intervals of 30 minutes, a comprehensive dataset of 432 accident scenarios is generated.

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

From the generated dataset with MAAP, a total of six parameters were chosen, and these are summarized in Table 1. These parameters encompass four pressure variables within the nuclear power plant and the temperatures associated with both the hot and the cold legs.

Considering the pivotal role of pressure increments within the reactor pressure vessel (RPV) rupture process, pertinent data encompassing the pressure metrics on the primary side, as well as the temperatures of the hot and the cold legs, were used as inputs for the artificial neural network. The inputs are expected to encapsulate a comprehensive overview of the accident's underlying dynamics.

The training dataset was derived from the MAAP dataset with the time interval of 30 minutes. Although the MAAP platform has the capability to generate data with elevated temporal granularity, the foresight led us to consider that the reduced temporal span between successive data instances could potentially impede the neural network's efficacy. This anticipation stems from the rationale that a more compact timeframe might yield a diminished magnitude of variation in the output data (RPV failure time) relative to a comparable array of input parameters.

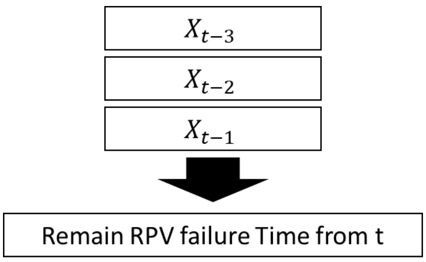

Figure 1 Concept of RPV Failure Prediction Model

Utilizing an artificial neural network for the prediction of RPV failure entails the incorporation of input parameters spanning three discrete time steps, each corresponding to a duration of 30 minutes per step, aimed at forecasting the time remaining until the imminent RPV failure. This framework is illustrated in Figure 1. To address this inquiry, the authors engaged in an investigation employing three distinct neural network architectures: CNN, LSTM, and the hybrid CNN-LSTM model. Each architecture was endowed with two concealed layers.

The complete dataset underwent a stochastic partitioning into approximate proportions of 8:1:1, designating them respectively as the training set, test set, and validation set. The training set is the reservoir of data employed for the direct training of the neural network. Within this study, the loss criterion utilized during the training process is the mean squared error metric. Conversely, the test set and validation set are held independent of the training process. The test set serves as the yardstick for evaluating the ultimate performance of the well-trained neural network.

The validation set, on the other hand, serves as a safeguard against overfitting during the network's training. Throughout the training process, the neural network scrutinizes the loss value concerning the validation set after each epoch, ceasing its training trajectory when the validation loss attains its minimal value and remains unaltered despite 100 subsequent epochs of training.

3. Results & Discussions

Table 2 presents the root mean square error (RMSE) corresponding to the predictive outcomes of the model for each dataset. Notably, the hybrid CNN-LSTM model demonstrates the best precision, as evident from the error assessment on the test set. This observation indicates that the successful and comprehensive model, which can be indicated by the relatively minimal disparity in RMSE values between the training and test sets. Figure 2 shows the distribution of the difference between the predicted value of each model and the actual MAAP data in the test set. It can be seen that lower standard deviation is shown according to the order of RMSE values for the test set 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

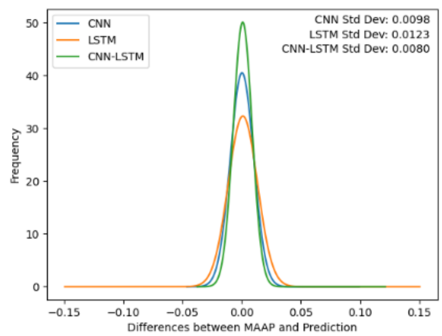

Figure 2 Distribution of Predicted Value of Test set

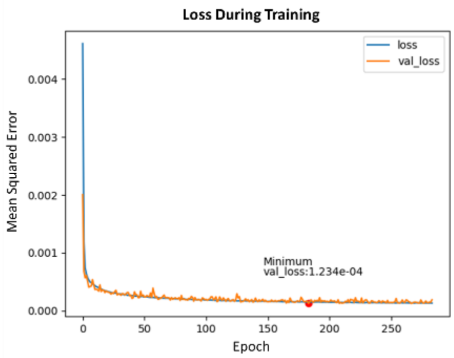

Figure 3 Training Loss of CNN model

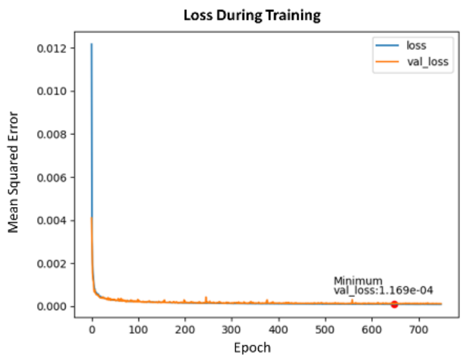

Figure 4 Training Loss of LSTM model

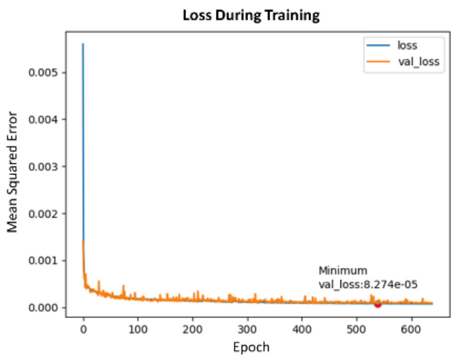

Figure 5 Training Loss of CNN-LSTM model

Figures 3, 4, and 5 illustrate the trajectory of loss values during the training phase for the CNN, LSTM, and hybrid CNN-LSTM composite models, respectively. In each case, a prominent pattern emerges whereby the loss consistently diminishes as the number of training epochs increases. It is of significance to note that the learning process adheres to the methodology delineated in the Methods section, wherein a decisive criterion for concluding the learning process is the observation that the minimum loss within the validation set remains unaltered for a continuous span of 100 consecutive epochs.

Figure 6 illustrates the cumulative root mean square error (RMSE) computed over the course of the accident while evaluating the RMSE associated with the test set. It is evident that predicting the time of Reactor Pressure Vessel (RPV) failure by leveraging information from the initial stages of the accident yields superior accuracy compared to utilizing information from later stages of the same accident.

This observation is expected due to the characteristics of the given dataset. A substantial portion of the data during the early phase of the accident exhibits a consistent pattern before the occurrences of RCP seal LOCA and HPI failure have not taken place. As the accident progresses and the events of RCP seal LOCA and HPI failure occur, better correlation between input data and output data emerges. This contributes to the enhancement of the model's predictability.

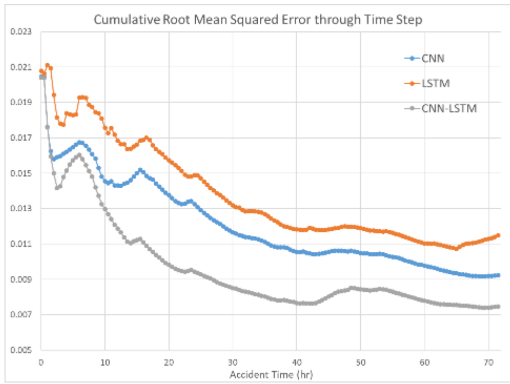

Figure 6 Cumulative RMSE vs. Accident Time

4. Summary & Further Works

In summary, this preliminary investigation, utilizing data derived from the selected accident scenarios within the TLOCCW context, demonstrates successful RPV failure time prediction with a commendable level of accuracy. Among the evaluated CNN, LSTM, and CNN-LSTM hybrid models, the CNN-LSTM hybrid model exhibited the most favorable performance.

Nevertheless, these models solely drew upon partial data originating from a relatively uncomplicated TLOCCW accident scenario. Consequently, a compelling necessity exists to extend the applicability of these models. Efficacy within scenarios encompassing not only RCP seal LOCA and HPI failure, but also additional pivotal components such as LPI, HX, CSS, and MDAFW pump malfunctions have to be monitored.

Importantly, these models were exclusively trained using data from accidents wherein RPV failure time was predetermined. It is imperative that subsequent research delves into the models' capacity to identify and generalize when training data does not contain RPV failures.

Acknowledgment

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