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Applicability Study of Deep Learning-Based Surrogate Model to Severe Accident Simulation

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1. Introduction

The field of nuclear safety has seen an increase in the application of PSA (Probabilistic Safety Assessment) methods, which are used to quantify the risk level of nuclear power plants. However, conventional PSA methods have a critical limitation in addressing time-dependent interactions, such as component failure timings or mitigation strategy implementation timings. This is due to the reliance on predefined sequences of safety system and operator actions, which are evaluated through limited thermal hydraulic code calculations using conservative conditions [1].

To overcome these limitations, Dynamic PSA has been developed, which incorporates various samples of operator action timings and component reliability into extensive thermal hydraulic simulations. However, this approach comes with high computational costs and limits the number of scenarios that can be simulated [2].

To improve the computational efficiency of Dynamic PSA, this paper proposes the use of deep learning. The proposed approach aims to approximate the thermal hydraulic code through deep learning. By utilizing this technique, the paper aims to provide a solution to the limitations posed by conventional PSA, while also improving computational efficiency.

2. Methodology and Result

2.1 Dataset Generation and Scope of Research

The dataset was produced by selecting a specific scenario and varying the timing of mitigation strategies for that scenario. TLOCCW (Total Loss of Component Cooling Water) with loss of auxiliary feedwater at Optimized Power Reactor 1000-type nuclear power plant (NPP) was chosen as the base case, and 2,000 cases in a 72-hour period were created by varying the timing of the implementation of each mitigation strategy using MAAP (Modular Accident Analysis Program) 5.03. Fig. 1 shows level 1 PSA event tree of TLOCCW in the reference NPP and the scenario used in this study. All the reactor coolant pump seals and other engineered safety features that are dependent on the component cooling water system as shown in Fig. 1., and Table I shows the means of mitigation strategies implemented.

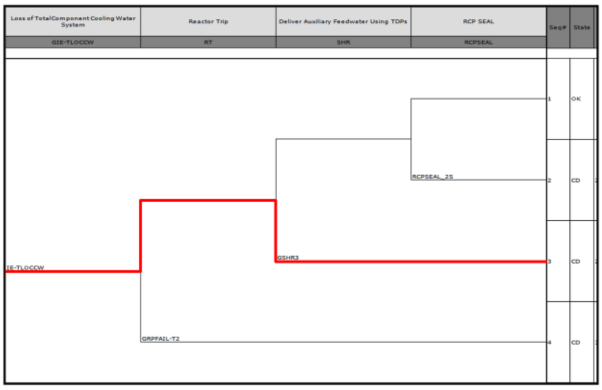

Fig. 1. Level 1 PSA Event Tree of TLOCCW and Scenario Used in this Research (Red Line) []

Table I: 3 Mitigation Strategies Used in Dataset

Mitigation Strategies	Mitigation Measures
Steam Generator Injection	Atmosphere Dump Valves Open
	External Injection
Reactor Coolant System Depressurization	Depressurization via a Power-Operated Relief Valve
Reactor Coolant System Injection	External Injection

Due to the limited scope of this study, which focuses on in-reactor phenomena during the applicability study phase, only three of the seven mitigation strategies outlined in the Severe Accident Management Guidelines (SAMG) were implemented as in-reactor mitigation strategies [3].

As an exploratory study of applicability, we aimed to investigate whether deep learning could generate a novel strategy sequence that deviates from the existing SAMG method, even though it does not fit within the confines of the SAMG Diagnosis flow chart.

2.2 A Deep Learning Model as a Surrogate for MAAP

Although MAAP has a relatively short analysis time compared to other severe accident analysis codes, it is still computationally expensive to simulate enormous scenarios. It is well established that deep learning models are universal function approximators [4]. Also, in a pre-trained deep learning model, inferences can be made in a fraction of the time (In this study, most inferences were made in less than seconds).

The surrogate model used in this study is composed of 7 layers of fully connected layers with batch normalization. 7 thermal-hydraulic parameters and 3 mitigation strategy switches of time t were injected into the neural network, and 7 thermal-hydraulic parameters at time t+1 were derived. 7 thermal-hydraulic parameters are shown in Table II.

Table II: 7 Thermal-hydraulic Parameters as Inputs and Outputs of Neural Network

Hot Leg Temperature
Cold Leg Temperature
Steam Generator 1 Pressure
RCS Pressure
Reactor Water Level
Core Exit Temperature
Steam Generator Downcomer Level

3. Results and Discussions

3.1 Performance of Surrogate Model

Rolling prediction refers to a technique in which a model makes predictions for a sequence of data points one at a time, with each prediction being based on the most recent data point as well as a specified number of previous data points. The performance of the surrogate model was measured with rolling prediction and mean average error. Fig. 2. Shows mean average error at each time step.

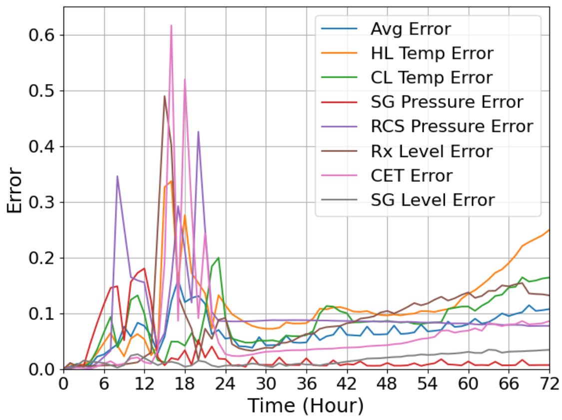

Fig. 2. Mean Average Error at each Time Step.

The error is largest at 18 hours, when the highest number of RPV fails occurred. It is believed that the model does not accurately predict the rapid pressure and temperature changes that occur as the RPV fails.

4. Conclusions

This paper proposes a deep learning approach to improve the efficiency of Dynamic PSA in the field of nuclear safety. The proposed method was applied to a specific scenario, TLOCCW, and the results demonstrated the potential of deep learning to improve the efficiency of Dynamic PSA although this study is a preliminary study prior to full-scale deep learning application and has many limitations. For further work, we will study how the surrogate model can predict rapid changes in temperature and pressure behavior.

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