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Machine Learning Prediction of Multiple Steam Generator Tube Rupture accident in APR1400

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1. Introduction

This study was conducted to deeply analyze the Multiple Steam Generator Tube Rupture (MSGTR) accident in the APR1400 reactor. To achieve this, a thermal hydraulic simulation model was created using the Best Estimate Plus Uncertainty (BEPU) method, followed by the development of a machine learning (ML) meta-model capable of forecasting the nuclear power plant's response during an accident scenario.

Following the Fukushima Nuclear Power Plant accidents in 2011, there has been a heightened interest in ensuring the safety of NPPs under extreme events that exceed the Design Basis Accidents (DBA). Consequently, the concept of Design Extension Conditions (DEC) was introduced to investigate the plant's ability to withstand multiple failures and severe accidents, as well as to develop potential mitigation strategies DEC accident scenarios include MSGTR, where more than one tube ruptures simultaneously in a single steam generator (SG). Similar to a single SGTR, contaminated reactor coolant leaks into the secondary side. Due to the break flow, the SG becomes pressurized, potentially leading to the opening of the main steam safety valve (MSSV) and the release of radioactive material into the environment. Compared to the SGTR scenario, the break flow in an MSGTR scenario is relatively larger. Thus, the accident progresses more rapidly, and the potential discharge of radioactive material is greater. Initial response and operator actions are crucial to mitigate potential consequences and bring the plant to safe shut down conditions. In this study, an MSGTR scenario involving the rupture of five tubes in APR1400 was analyzed, based on work already completed by Dzien [1] and Bae [2].

Although the safety analysis for APR1400 in the Design Safety Document was conducted using a conservative approach, the IAEA recommends the Best Estimate Plus Uncertainty (BEPU) approach as a tool for a more realistic safety assessment. This method enables the determination of an NPP response that is both credible and reliable, taking into account various uncertainties that can considerably impact the progression of an accident. The outcomes of the BEPU analysis result in a more substantial safety margin, thereby allowing for a more flexible and cost-effective operational framework for the NPP. This particular methodology has been effectively employed for the purpose of reactor licensing, in addition to numerous scientific studies. These include the DEC analysis, which has been utilized in countries such as France and China. For these reasons, the BEPU approach was applied in this work to analyze the MSGTR accident scenario, mitigation strategy, and evaluation of operator action.

In recent years, there has been a surge of interest in Artificial Intelligence (AI). One of its promising applications lies in predicting accidents in NPPs. Additionally, the concept of virtual twins is gaining traction, offering virtual replicas of physical assets or systems that can simulate real-world scenarios for testing, optimization, and predictive maintenance. These advancements underscore AI's potential not only in risk mitigation but also in revolutionizing how we simulate and manage complex systems, thereby assisting operators in making informed decisions critical to operational safety and efficiency. The completed project represents a step towards integrating AI into safety analysis and ensuring the secure operation of NPP.

2. Methodology

The workflow for the model development was divided into several stages. First, the MSGTR accident was simulated in the APR1400 model using the MARS best-estimate thermal hydraulic system code. Next, an uncertainty quantification analysis was conducted. To achieve this, the statistical software DAKOTA was coupled with the MARS code. This procedure was necessary to evaluate key uncertainties related to the MSGTR accident, derive results that satisfy the USNRC 95/95 rule using Wilks' equations, and generate a database for ML model development. In the final step of the project, three ML models capable of predicting the APR1400 response to an MSGTR scenario were built and trained.

2.1 MSGTR accident simulation

To simulate the accident, a thermal hydraulic model of the APR1400 developed using the MARS-KS code was employed. Nodalization of the reactor is shown in Figure 1. The accident was simulated by assuming that the rupture occurs at 0 seconds, with five U-tubes instantaneously rupturing on the hot-leg side of the SG. The rupture was modeled as a double-ended guillotine break. In contrast to the single tube rupture, the simultaneous five-tube rupture was modelled by increasing the rupture area by a factor of five. The location of the break on the hot leg side has been shown to potentially result in the shortest MSSV opening time and the largest discharge flow [3]. The rest of the initial conditions were set as close as possible to APR1400 nominal conditions as shown in Table 1 to reflect realistic operating conditions, following the BEPU methodology.

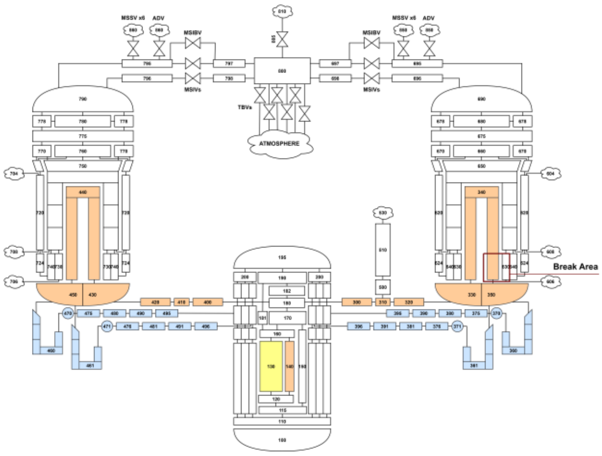

Figure 1: MSTGR in APR1400 nodalization

Table 1: Simulation Initial Conditions

Parameter	**Unit**	**Value**
Core Power Level	MWt	3983.00
Hot-leg Temperature	K	595.07
Cold-leg Temperature	K	562.63
PRZ Pressure	kg/cm2	157.36
PRZ Water Level	%	57.4
Core Mass Flow Rate	106kg/hr	76.7
SG Pressure	kg/cm2	68.87

Given the rapid development of an MSGTR accident, prompt and appropriate operator actions are crucial for event mitigation and ensuring the safety of the plant. A key time for each required operator action has been derived and evaluated by Bae [3]. Accordingly, based on Young's timeline, the first operator action was modeled to be implemented 10 minutes after the reactor trip as a manual trip of the RCP. After another 5 minutes, a temporary RCS cooldown operation should be performed by manual operation of the Main Steam Isolation Bypass Valve (MSIBV) and Steam Blowdown Control System (SBCS) to discharge steam from the affected SG to the condenser. The sequence and timing of these modeled operator actions, along with all other necessary actions and their respective times, are systematically outlined in Table 2.

Table 2: Operator Actions Timeline

Timeline	Operator Action
0.0s MSGTR initation	-
Reactor trip	-
Rx trip + 10min	OA#1 Manual trip of 4 RCPs
Rx trip + 15min	OA#2 Temporary RCS cooldown by manually opening MSIBVs and TBV.
OA#2 + 2min	OA#3 Pressurizer Auxiliary Spray operation
OA#3 + 2min	OA#4 Manual closing of MSIBVs and TBV
OA#4 + 2min	OA#5 SGBD operation (200s)
OA#5 + 2min	OA#6 Manual opening of ADV in unaffected SG
OA#6 + 1hr	OA#7 Restarting one RCP per loop

2.2 Uncertanity Quantification Framework

For uncertainty quantification, the thermal hydraulic input decks for MARS-KS were coupled with DAKOTA software using Python scripts to manage data transfer. The Phenomena Identification and Ranking Table (PIRT) was developed based on studies by Westinghouse [4] and Ahn [5] for SGTR accidents, with Youn [6] focusing on the MSGTR scenario for APR1400 reactors. As shown in Table 3, for MSGTR 12 most important phenomena were selected, along with 13 normally uncertain parameters and 19 uniformly uncertain parameters, each with specified ranges.

Table 3: PIRT for MSGTR scenario

Phenomena	**Parameter**	**PDF**	**μ**	**σ**	**min –max**
Decay heat fuel up	Reactor power	Normal	1	0.008	0.98-1.02
	Subchannel area	Normal	1	0.025	0.95–1.05
	Gap conductance	Normal	1	0.18	0.64-1.36
	Fuel thermal conductivity	Normal	1	0.05	0.90-1.10
	Fuel heat capacity	Normal	1	0.01	0.98-1.02
	Fuel pallet diameter	Normal	1	0.04	0.092-1.08
	Cladding thermal conductivity	Normal	1	0.05	0.998-1.006
	Decay heat	Uniform	1		0.90-1.10
Mixture vessel	Initial PZR pressure	Uniform	1		0.94-1.026

pressure heating	Initial PZR inventory	Uniform	1		0.59-1.449
Saturation condition in HL	Inlet temperature	Uniform	1		0.97-1.003
	Multiplier for liquid Dittus-Boetler correlation	Uniform	1		0.85-1.15
	Multiplier for Chen nucleate boiling model	Uniform	1		0.8–1.2
	Multiplier for vapor Dittus-Boetler correlation	Uniform	1		0.8–1.2
	Initial total mass flow	Uniform	1		0.95–1.05
	RCPs moment of intertia	Normal	1	0.1	0.8-1.2
SIP	Safety injection delay time	Uniform	1		0.85-1.125
	IRWST temperature	Uniform	1		0.96-1.064
Break flow	Brek area	Uniform	1		0.95-1.05
	Break discharge coefficient	Uniform	1		0.60-1.40
Collapsed water level, flashing fraction	Initial secondary-side pressure	Uniform	1		0.974-1.026
	Initial SG inventory	Uniform	1		0.55–1.474
	Interphase heat transfer coefficient	Uniform	1		0.9–1.1
Condenser steam flow rate	Outlet pressure	Normal	1		0.974–1.026
MSIV steam flow rate	MSIS setpoint	Uniform	1	0.09	0.9–1.1
MSIBV steam flow rate	Steam flow rate	Uniform	1	0.09	0.9–1.1
ADV steam flow rate	Outlet pressure	Normal	1	0.09	0.9–1.1
Auxiliary spray flow rate	Flow rate	Uniform	1	0.09	0.9–1.1
Auxiliary feedwater	Flow rate	Uniform	1		0.77-1.23

The number of iterations was determined using Wilk's k-order formula. Choosing Wilks' method for this study was driven by its simplicity, accuracy, and acceptance in regulatory contexts. According to Wilks' one-sided 5th order formula, 181 samples are adequate to meet the tolerance limit specified by the USNRC 95/95 rule. The results of each iteration were then stored in a MySQL database due to the large amount of data that would not fit into standard CSV files. Using the same method, a database consisting of 800 samples was generated, which served as training data for machine learning models.

2.3 Machine Learning models development

To address the problem outlined in the Introduction section, GRU, LSTM, and CNN-LSTM models have been developed to predict the plant response during an MSGTR scenario. The models were adapted for forecasting a single key thermohydraulic parameter based on 24 other parameters during the progression of the accident.

The foundation for training ML models is the database, which enables models to learn and memorize dependencies. Since it's impossible to replicate nuclear power plant accidents in real life, simulation data has been utilized for this purpose. The aim of the ML models was to predict RCS temperature, RCS pressure, and RVUH void based on other parameters during an MSGTR accident. The parameters for the database were selected using Spearman's correlation coefficients with the three mentioned parameters. Next, for all three targets, common parameters were selected where the absolute value of correlation was greater than 0.25. In this way, a universal list of 24 parameters was obtained. Then, following the methodology described previous section, an 800-sample database containing 11 200 800 lines and 25 columns was generated (time was 25th parameter). Based on trial and error methods, hyperparameters were adjusted to achieve optimal accuracy and efficiency of the model. The lengthy duration of each simulation iteration (14000 seconds) resulted in a large database that posed computational challenges during processing and training. Following training, the models were evaluated using various performance metrics including Mean Absolute Error (MAE), Mean Square Error (MSE), Root Mean Square Error (RMSE), coefficient of determination (R^2), and prediction accuracy.

Table 4: Hyperparamters of ML models

Hyperparametres	**GRU**	**LSTM**	**CNN+LSTM**
Optimizer	Adam	Adam	Adam
Epoch	10	10	10
Batch size	700	700	700
Activation function	relu	relu	relu
Hidden layers	1	1	2
Kernel regularizes	1	1	1
Training sample	8316584	8316584	8316584
Testing sample	2072138	2072138	2072138

Additionally, it was a trail to employ Explainable Artificial Intelligence (XAI) techniques, namely SHAP and LRP to address the "black box" nature of AI and enhance the trust in meta-model predictions for applications relevant to the nuclear safety industry

3. Results

3.1 MSGTR accident simulation using BEPU method

Figures 2-4 illustrate the NPP system response under MSGTR accident conditions, considering various uncertainty sources described in the PIRT, as shown in Table 2. The analysis focused on key safety parameters, including RCS pressure, RCS temperature, and RVUH void fraction. Among all simulated iterations, only in four instances did the plant not reach the SCS entry condition within the initial 14,000 seconds. The RVHU void fraction was reduced in all cases. In Figure 2, we can observe a group of simulations where the pressure initially drops only slightly, then returns to nearly the same level as the initial value after approximately 1000 seconds. This group of simulations starts with a relatively low water level in the pressurizer and a high water level in the affected steam SG, which are conservative initial conditions for the case. This combination of parameters caused a reactor trip, isolation of the affected SG due to the high water level, and activation of the SIP due to the low water level in the pressurizer after approximately 60 seconds, almost simultaneously. The early isolation of the affected SG also led to a decline in heat removal and an accumulation of heat, which is evident in Figure 3. Simultaneously, high pressure in the affected SG caused the opening of the MSSVs. However, the pressure was only successfully reduced after the operator opened the MSBVs and the TBV. Another group of curves represents medium drop in RCS pressure within the first 1000 second. Initial conditions for those simulations included an average water level in the pressurizer and a high water level in the affected SG. The noticeable drop (smaller than in the nominal case) is caused by the early MSIS and isolation of the affected SG. Although, the initial RCP pressure was higher than in the previous group of curves, allowing the primary side to handle the cooling restriction more steadily. For this group of cases, the MSSVs were also opened. The irregular shapes of the RCS pressure and RCS temperature plots indicate different sequences of events during the simulations, highlighting the need for further UQ analysis. Additionally, each individual case where the plant did not reach the SCS entry conditions within the initial 14,000 seconds should be considered separately. The opening of the MSSVs also warrants attention due to the potential for radioactive release, necessitating radiological analysis. Despite the various sequences of events, operator actions successfully mitigated the accident in a timely manner in most cases, and the SCS entry conditions were met.

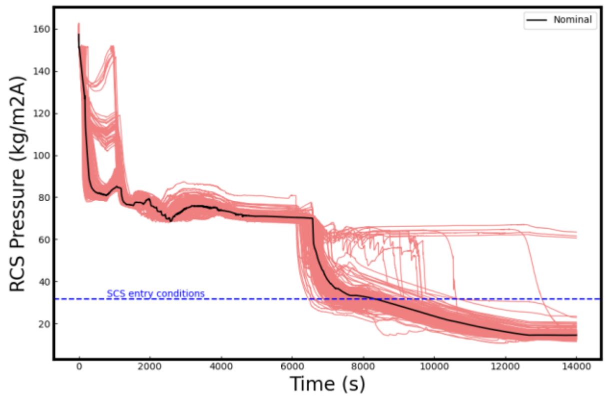

Figure 2: MSTGR results for RCS Pressure vs Time

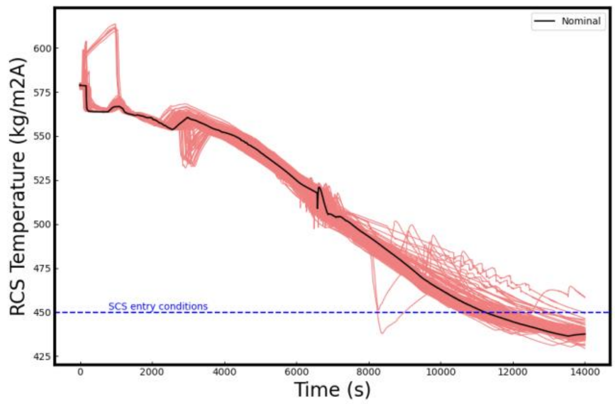

Figure 3: MSTGR results for RCS Temperature vs Time

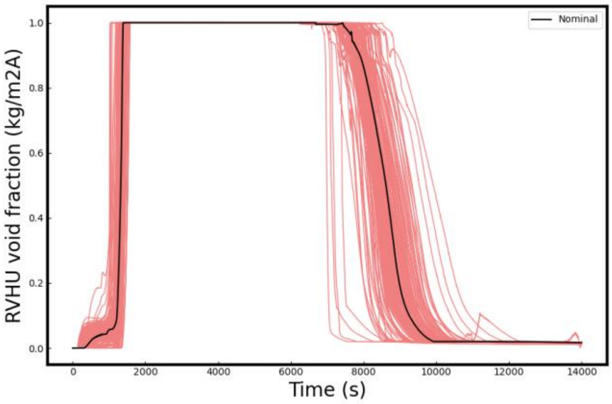

Figure 4: MSTGR results for RVHU void fraction vs Time

3.1 Machine Learning prediction results

The collected results of the fitted and evaluated models are summarized in Table 5. All models demonstrated excellent predictive capabilities, consistently achieving accuracy over 97%. Changing the forecasting parameter did not affect the model's learning capabilities; it remained flexible and adapted to new conditions. The biggest challenge during model training was the long fitting time due to operating on a large dataset. Based on this criterion, the LSTM model was deemed impractical because its time step was the longest, reaching up to 70.7 ms/step. Training this model took over an hour. In most cases, the fastest learning model was LSTM-CNN, which is why it was considered the best and most practical. As depicted in Figures 5-7, the forecasting capability of parameters by the models was excellent. The only deviations observed were in the LSTM model's prediction of RCS Pressure. Additionally, it was noted that during the training of models, slightly different values of training time and accuracy were obtained multiple times.

Table 4: Models Performance Results

Parametr	**Model**	**Accuracy (%)**	**Step Time (ms/step)**
RCS Pressure	GRU	99.34	21.9
	LSTM	98.29	70.7
	CNN+LSTM	98.77	30.0
RCS Temperature	GRU	97.36	29.1
	LSTM	97.11	43.7
	CNN+LSTM	98.97	10.8
RVUH Void	GRU	97.89	42.5
	LSTM	98.44	72.3
	CNN+LSTM	98.85	25.5

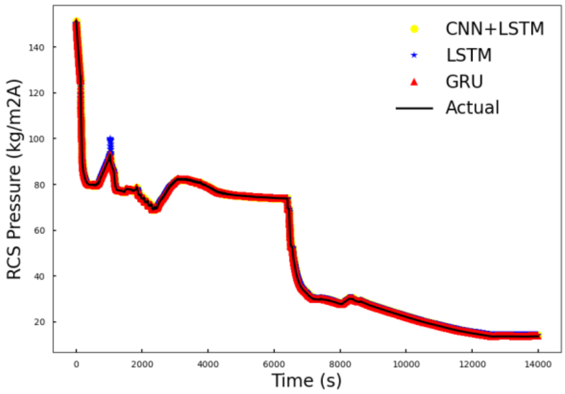

Figure 5: Predicted and Actual Values of RCS Pressure

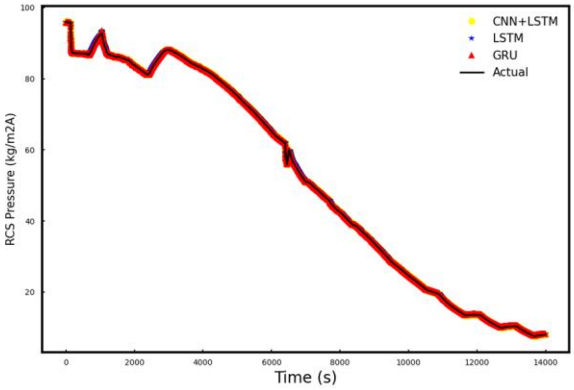

Figure 6: Predicted and Actual Values of RCS Temperature

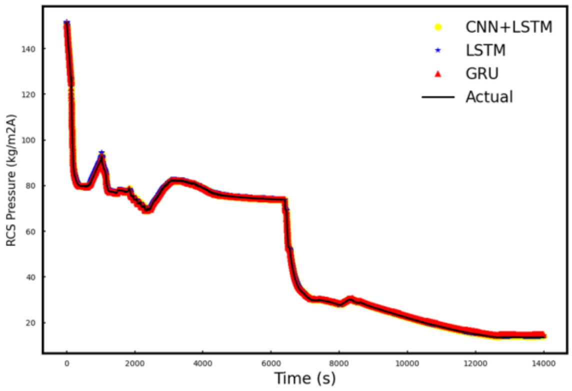

Figure 7: Predicted and Actual Values of RVUH void fraction.

4. Conclusions

In the above study, a MSGTR accident scenario in the APR-1400 reactor was simulated. The study considered operator actions necessary for accident mitigation and various sources of uncertainty affecting the accident progression. The BEPU methodology analysis demonstrated that with specific operator actions at critical timelines, the power plant remains safe in most of cases. However, due to the varied shapes of plots of plots presenting simulation results with uncertainty quantification, suggesting different potential sequences of events, further investigation of the accident should be pursued. The logic of simulation modeling and the PIRT table should be revised again. Additionally, in cases where MSSVs have been opened, radiological analysis is necessary.

The results of the study were used to train three ML models - GRU, LSTM, and CNN-LSTM. All three models were able to accurately predict RCS pressure, RCS temperature, and RVUH void fraction as the accident progressed. Despite all models achieving excellent predictive capabilities, they required a significant amount of time for fitting and computational power. Consequently, the LSTM model, with the longest training time, was deemed impractical, whereas the LSTM-CNN model, with the shortest average training time, was considered the best. During multiple training sessions, the models achieved varying accuracy results ranging from 97% to 99.8%. It is essential to classify this uncertainty to enhance the credibility of the models by using special build BNN model. To enable the use of models in safety analysis, XAI techniques should also be applied to demonstrate the prediction-making process.

5. Acknowledgement

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REFERENCES

[1] Sebastian Dzień , Aya Diab, “Safety evaluation of Multiple Steam Generator Tube rupture accident using the best estimate plus uncertainty approach”, Nuclear Engineering and Design, Volume 422, June 2024, 113150

[2] J.-H. Bae, S.-S. Jeon, J. Bang, D.-H. Hwang, “Operator actions evaluation for MSGTR accident mitigation”, Annals of Nuclear Energy (2022)

[3] J.-H. Jeong, K.-S. Chang, S.-J. Kim, J.-H. Lee, “Best-estimate analysis of MSGTR event in APR1400 aiming to examine the effect of affected steam generator selection”, Journal of the Korean Nuclear Society (2002)

[4] G.E. Wilson, C.D. Fletcher, C.B. Davis, “Phenomena identification and ranking tables for westinghouse AP600 small break loss-of-coolant accident, Main steam line break, and steam generator tube rupture Scenarios”, United States (1997)

[5] S.H. Ahn, C.W. Huh, J.Y. Park, M.W. Kim, Y.J. Cho, “Phenomena identification and rankings in domestic PWR accident conditions”, KNS, Spring Meeting, Gyeongju (2008)

[6] B.-S. Youn, J.-H. Koh, D.-H. Lee, “Development the DEC PIRT for APR1400 MSGTR”, Transactions of the Korean Nuclear Society Spring Meeting, Jeju (May 2017)