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A Systems Engineering Approach for Predicting NPP Response under Steam Generator Tube Rupture Conditions using Machine Learning

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Abstract : Accidents prevention and mitigation is the highest priority of nuclear power plant (NPP) operation, particularly in the aftermath of the Fukushima Daiichi accident, which has reignited public anxieties and skepticism regarding nuclear energy usage. To deal with accident scenarios more effectively, operators must have ample and precise information about key safety parameters as well as their future trajectories. This work investigates the potential of machine learning in forecasting NPP response in real-time to provide an additional validation method and help reduce human error, especially in accident situations where operators are under a lot of stress. First, a base-case SGTR simulation is carried out by the best-estimate code RELAP5/MOD3.4 to confirm the validity of the model against results reported in the APR1400 Design Control Document (DCD). Then, uncertainty quantification is performed by coupling RELAP5/MOD3.4 and the statistical tool DAKOTA to generate a large enough dataset for the construction and training of neural-based machine learning (ML) models, namely LSTM, GRU, and hybrid CNN-LSTM. Finally, the accuracy and reliability of these models in forecasting system response are tested by their performance on fresh data. To facilitate and oversee the process of developing the ML models, a Systems Engineering (SE) methodology is used to ensure that the work is consistently in line with the originating mission statement and that the findings obtained at each subsequent phase are valid.

Key Words : Recurrent Neural Network (RNN), Long Short Term Memory (LSTM), Gated Recurrent Unit (GRU), Convolutional Neural Network (CNN), Machine Learning (ML), Best Estimate Plus Uncertainty (BEPU)

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1. Introduction

In recent years, machine learning (ML) and particularly deep learning have attracted a lot of attention due to their numerous remarkable advancements in perceptual areas that were previously believed to be limited to humans such as image classification, speech recognition, digital assistants, ad-targeting, etc..[11] One area where the strength of neural networks in handling large amounts of data has been increasingly exploited is time-series forecasting. This ability can be utilized in nuclear engineering to forecast important safety factors accurately, quickly, and reliably for accident management. Additionally, ML can be used to perform various nuclear simulations - such as thermal-hydraulic uncertainty quantification in this case - at a significantly lower cost and in a much shorter time.

The present analysis centers on a Steam Generator Tube Rupture (SGTR) with a concurrent loss of offsite power (LOOP). SGTR accident scenario is unique in that it has the potential to create a direct line of fission release to the environment with the mixing of primary and secondary coolant combined with steam discharge through the Main Steam Safety Valves (MSSVs). Following the Fukushima accident, the Korean Government added to its regulatory guidelines for severe accident management plants that radiation limits at the boundaries of plant sites should be less than 250 mSv.[8] The possibility of containment bypass due to SGTR has become a significant concern as it accounts for more than half of the likelihood of direct radiation release to the environment according to probabilistic safety analysis. There have been 11 occurences of SGTR including one incident at Hanul unit 4 OPR100 NPP in 2002.[8] SGTR can be the result of multiple degradation processes leading to wall thinning, tube cracking, and mechanical defects, or it can be thermally induced by accident conditions leading to superheated steam circulating in hot legs. This analysis considers the scenario of a spontaneous guillotine break on one U-tube leading to rapid primary-to-secondary side leakage and a resultant increase in secondary pressure.

2. Objective

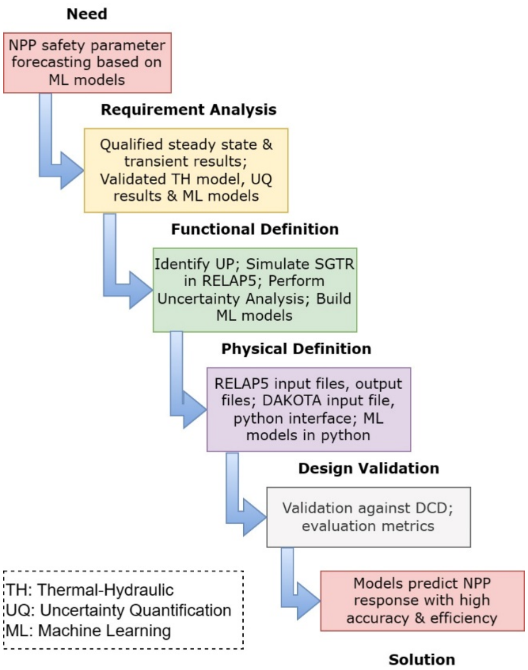
The goal of the study is to develop robust ML models harnessing the flexibility and strengths of neural networks to make predictions on system response under SGTR accident conditions with high accuracy and efficiency.

This paper demonstrates how a Systems Engineering approach was adopted as a guiding structure for the consistent, and efficient realization of the project each step of the way.

Specifically, the Kossiakoff method of Systems Engineering[1], comprised of four successive steps as shown in Figure 1, is used in this work to arrive at the stated objective.

1. Requirement analysis (Problem definition)
2. Function definition (functional analysis and allocation)
3. Physical definition (synthesis, physical analysis, and allocation)
4. Design validation (verification and

evaluation)

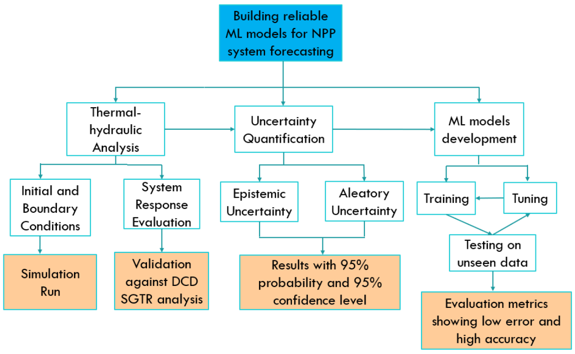


[Figure 1] Engineering Method

According to the SE approach, the first step in effectively planning and managing a project is to identify the various stakeholders, their needs, and requirements. Next, the system architecture must be developed, and a set of verification and validation activities must be created to make sure all requirements are satisfied by predetermined success criteria at each stage of development. An activity hierarchy was developed to identify and keep track of the most important characteristics relevant to the overarching mission of the project.

3. Work Breakdown Structure

After the hierarchy is established, the project is split into manageable tasks. The work breakdown structure outlines the steps involved in bringing the project to fruition. Work breakdown structure involves the following steps, which can be further split into two groups: thermal-hydraulic model development (steps 1-4) and ML model development (steps 5-9). For the sake of brevity, the description of each task is reduced to its essentials. The sections that follow offer additional details.



[Figure 2] Activity Hierarchy Work Breakdown Structure

1. Construct and validate the steady-state APR1400 model with initial conditions matching the conservative assumptions employed in DCD SGTR accident analysis using the simulation tool RELAP5/MOD3.4
2. Simulate SGTR transient conditions in RELAP5/MOD3.4. Results of key parameters are once again compared to those reported in the DCD to ensure reasonable agreement and therefore validate the thermal-hydraulic model.
3. Identify uncertain parameters important for the scenario and gather their statistical information expressed by the probability density function (PDF)

4. Perform uncertainty quantification by loosely coupling RELAP5/MOD3.4 and DAKOTA. Uncertainties are propagated based on their PDF. Uncertainty bands for key system response are obtained as a result.
5. Selecting architecture for ML models development based on their applicability to predict NPP response accurately, at the same time, cutting down on costs and time.
6. Data-preprocessing which consists of normalization, splitting (into three categories as is the standard for ML: training, testing, and validation), and transformation into the appropriate 3-D structure.
7. Hyper-parameters selection and tuning to optimize performance and minimize the loss function.

Models make predictions on data it has never seen before (test data). Any discrepancies between predicted values and actual values are observed and quantified, along with learning curves for each model to show a complete picture of the performance of each model.

4. Requirements Development

The requirements of this work can be categorized into four groups: mission requirements, originating requirements, system requirements, and component requirements as summarized in Table 2.

<Table 1> Model Requirements

Requirements	Descriptions
Mission Requirements	• ML models shall predict NPP response under SGTR conditions accurately, efficiently, and quickly.
Originating Requirements	• UQ Model: Uncertainty band within 95/95 tolerance limits, identify most probable response from results post-processing uncertainty analysis. • ML Model: checked using evaluation metrics.
Systems Requirements	• Guillotine break on U- tube. • Offsite power is unavailable. • Reactor Coolant Pumps are unavailable. • Control system actuations during the transient are assumed to be at nominal setpoint values. • Passive safety systems are available. • Transient calculation lasts 30 minutes. • No operator action is included in the analysis.
Component Requirements	• The codes must be able to give a detailed representation of thermal-hydraulic and reactor kinetics phenomena. • The simulation model must resemble actual plant behavior both during steady state and SGTR transient. • Uncertainty quantification framework must be followed closely and take all uncertain parameters that best represent the governing phenomena into account. • ML models must be accurate, precise, and efficient.

The mission requirements reflect the need to have multiple validated ML models with the capacity and potential to provide valuable assistance and act as an additional guiding tool in emergencies. The model shall perform accurately, efficiently, and robustly using a purely data-driven approach. The results obtained shall be replicable through various runs. Lastly, ML model should perform more quickly than the physics-based model.

The originating requirements are thus derived from the mission requirements. To accomplish the mission requirements, the ML models must have a large reservoir of knowledge/database about every possible scenario related to SGTR built on realistic assumptions and after accounting for all sources of uncertainties. This can be done using uncertainty quantification (UQ). The requirement for UQ results is to satisfy the 95/95 tolerance limit. While the requirement for ML models is based on the evaluation of ML results and performance metrics.

System requirements detail the assumptions and constraints placed on the NPP system for the SGTR scenario being considered. These requirements act as the basis for safety analysis and ensure the results are comparable to those listed in the APR1400 Design Control Document.

Component requirements outline standards for selecting a suitable simulation tool to guarantee that the model constructed obtains a reasonably high degree of accuracy and realistic results. RELAP5/MOD3.4 calculates equations of state, reactor kinetics, transport of non-condensable gases, and fluid behavior to determine the overall Reactor Coolant System (RCS) thermal-hydraulic phenomena. The code package RELAP5/MOD3.4 has been used by the US Nuclear Regulatory Commission (USNRC) to conduct safety analysis for licensing and continues to enjoy wide usage within the nuclear safety community. Numerous benchmark experiments have been conducted over the years to verify the code's ability to execute best-estimate plus uncertainty quantification, which seeks to replicate NPP behavior as closely as possible.

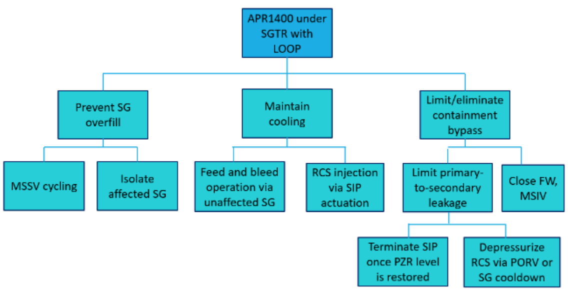
At the same time, the ML architecture selected to carry out the project should be capable of handling large datasets as well as benefiting from the enhanced scale and dimensionality of said data. Notably, it should be able to solve sequence problems, learn from the past, remember the patterns over long continuous sequences and selectively apply what it learns to predict future values. A final requirement is the ML architecture of choice should have the capacity to discern non-linear relationships embedded in the data. These factors suggest that the recurrent neural networks of LSTM, GRU, and CNN-LSTM, could yield successful results.

5. System Architecture

This subsection describes the functional and physical architecture in relation to the stated requirements. This relationship is summarized in Table 2.

5.1. Functional Architecture

Functional architecture describes the main function of safety and non-safety related NPP systems in an SGTR scenario to limit the radiological consequences of the accident and avoid progression into more severe accident conditions. Overall, it encompasses three main functions: prevent SG overfill, maintain cooling, and limit containment bypass. First, Main Steam Safety Valves open on the affected Steam Generator (SG) to offset the sudden spike in secondary pressure due to incoming primary coolant and closing of Turbine Control Valve. Over the longer-term, operator action is taken to completely isolate the affected SG to stop the collapsed water level from rising leading to coolant overfilling SG, and infiltrating the Main Steam Line, failing both the Main Steam Line and the Main Steam Safety Valve which will have grave consequences. Secondly, core cooling must be maintained at all times to avoid the entrance of severe accident conditions. Thirdly, containment bypass shall be minimized or entirely avoided when action is taken to ensure no part of the secondary pressure boundary is breached, and primary-to-secondary leakage is kept to a minimum. The details of each NPP function are shown in Figure 4. It should be noted that only automatic functions are reflected in the thermal-hydraulic model.



[Figure 3] Functional Architecture

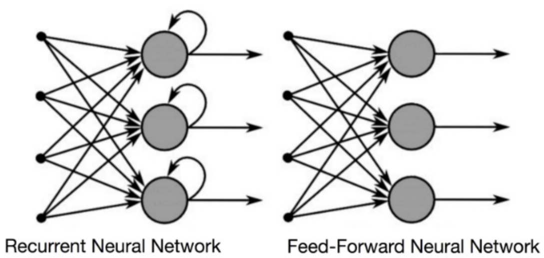
ML models' functional architecture covers the stages of development, validation, and deployment of the model to make accurate predictions on key parameters as a function of time. The development consists of two initially separate phases that can be carried out in parallel with each other: first, the selection of appropriate ML architecture and the construction of a bare model with the attendant components i.e. network topology and hyper-parameters; and second, data generation via thermal-hydraulic uncertainty quantification and data pre-processing. Naturally, these two phases then coalesce for the model training on available data, optimization of network structure, tuning of hyper-parameters, and validation of future predictions.

<Table 2> Functional and Physical Architecture

Requirements	Functional Architecture	Physical Architecture
Steady-state validation	Safety and non-safety components for normal operation	RELAP5 steady-state input
Transient validation	Components related to SGTR	RELAP5 transient input
Uncertainty quantification	Uncertainty sampling & propagation	DAKOTA input, python interface, RELAP5 adjusted input
NPP forecast based on ML model	ML model development, training and testing	Dataset from UQ, LSTM, GRU, CNN-LSTM architecture written in python, Talos optimization tool

5.2. Physical Architecture

The physical architecture entails NPP systems and components available during the SGTR scenario. These systems ensure the functional architecture is carried out. The details of the APR1400 model will be described in more detail in Section 7. Components playing a prominent role in SGTR with LOOP transients are Reactor Coolant Pumps (RCP) and Safety Injection Pumps (SIP) on the primary side. The coastdown of RCPs contributes to decay heat accumulation and worsening accident consequences while SIPs serve to recover the Pressurizer level and maintain core cooling. On the secondary side, significant components include the MSSV, Turbine−driven Auxiliary Feedwater Pumps (TDAFW), Main Steam Isolation Valve (MSIV), and Turbine Control Valve (TCV). MSSV is the main means of steam removal. MSIV acts to isolate the affected SG. TCV isolates the turbine from the rest of the system and TDAFWs on the intact SG facilitate the feed and bleed operation which is the main method of heat removal of the RCS to bring it to safe shutdown conditions. APR1400 system is described using the code RELAP5/SCDAP to accurately simulate the plant's response under both steady−state and transient conditions.



[Figure 4] Neural Network Architecture

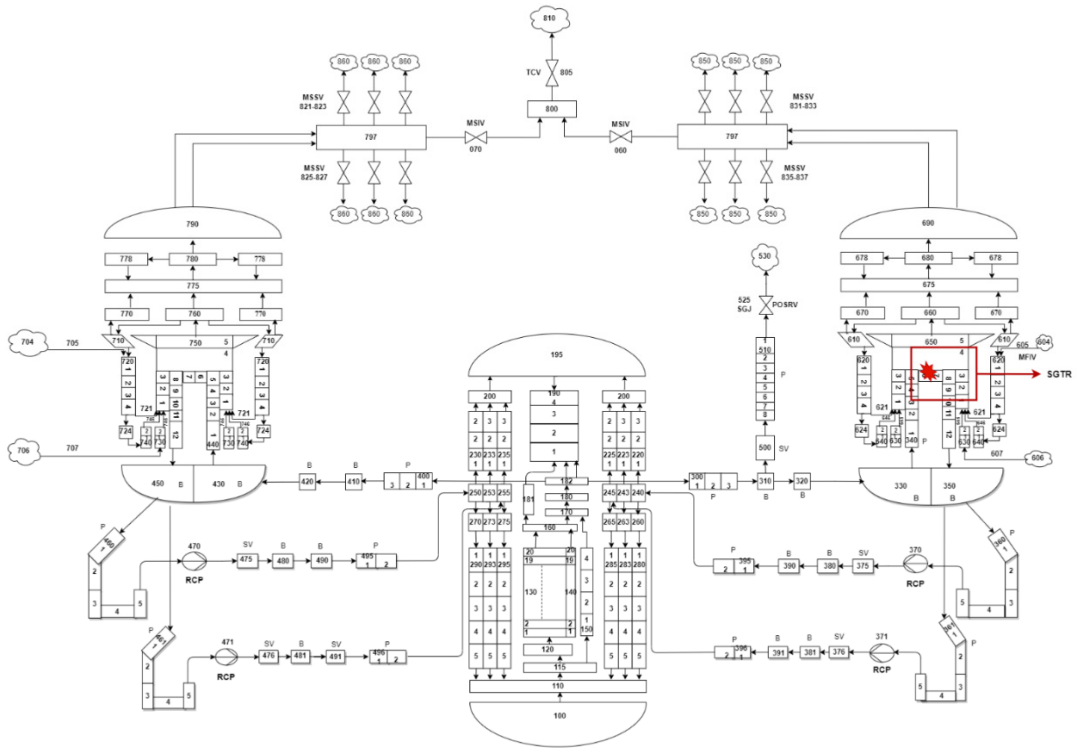
The physical architecture of neural networks is shown in Figure 4 with RNN (left) and ANN (right). Similar to Artificial Neural Network (ANN), RNN consists of an input layer, several hidden layers, and an output layer each made up of a varying number of neurons closely connected to process any given information and detect the governing mathematical structure. The network utilizes a system of weights, biases, and feedback signals to uncover the mathematical structure of the input data and extrapolate future values based on these well−learned patterns. The unique feature of RNN lies in a feedback loop on each layer to account for not only the current input but also information from previous sequences, storing it in what is called a 'hidden state'. This hidden state is passed and updated subsequently through each successive layer, as weights and biases are shared across the entire network, to accomplish the same prediction task. RNN's internal memory makes it the preferred option for solving sequential problems. It should be noted that ML models employed in the current work are more advanced variations on RNN architecture (i.e. LSTM, GRU & CNN−LSTM) which use gated mechanisms to enable selective memorization and long−term dependencies.

6. Thermal-Hydraulic Model

As mentioned earlier, the first phase of the project involves using the best−estimate code RELAP5/SCDAP3.4 to simulate NPP response under the SGTR scenario with LOOP. Results of steady-state and transient calculations are compared with DCD analysis to ensure the validity of the model. The nodalization of the employed model is provided in Figure 5.

The model consists of the Reactor Coolant System (RCS) on the primary side and two Steam Generators (SG) on the secondary side. Main components within the RCS include Reactor Pressure Vessel (RPV), 4 cold legs and 2 hot legs, and the Pressurizer (PZR) connected to one of the hot legs via a Surge Line. The coolant is circulated through the RCS via 4 Reactor Coolant Pumps (RCPs), one on each cold leg. The Pilot-Operated Safety Relief Valve (POSRV) on top of the PZR is connected to the containment to provide rapid depressurization for RCS in emergencies, although this function will not factor in the present analysis.

The secondary system represents the two loops, each including a steam Generator (SG) that houses the u-tubes which act as an interface across which the heat is transferred from the primary to the secondary side. The SGs are connected to the turbine through the Main Steam Lines (MSLs) hosting 2 Main Steam Isolation Valves (MSIVs), 10 Main Steam Safety Valves (MSSVs), 2 Turbine Control Valves (TCVs), and 2 Atmospheric Dump Valves (ADVs) which are also connected to a time-dependent volume representing the containment. The MSIVs halt the flow of steam from the SGs to the turbine while MSSVs modulate SGs pressure within the safety range. The TCV isolates the turbine from the rest of the system when the reactor trips whereas the ADV allows the operators to perform manual depressurization on the secondary side. The Auxiliary Feedwater (AFW) system is also modeled to replenish



[Figure 5] APR1400 Nodalization

the SGs once the water level drops below the setpoint. The main feedwater system (MFWS) is lost under loss of offsite power (LOOP). The turbine is represented as a boundary condition using a time-dependent volume.

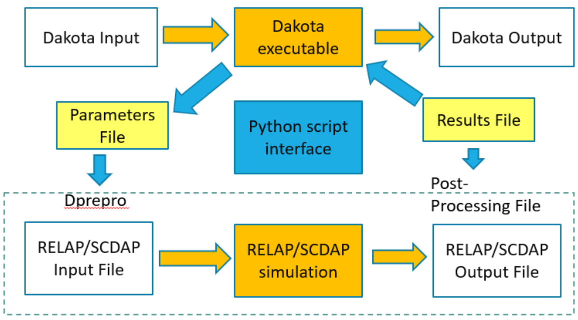
The break is simulated using a variable trip connecting one volume on the SG tube side with one volume on the SG shell side. To initiate the accident, this trip is activated at the beginning of the transient calculation.

7. Accident Description

SGTR is an initiating event that results in a decrease in RCS inventory. It shares some common characteristics with a loss-of-coolant-accident (LOCA) such as a decrease in Pressurizer (PZR) pressure and PZR level. But SGTR differs in that containment conditions remain unchanged while the secondary side indicators show signs of abnormalities i.e. rising water level in affected SG level and secondary pressure spike resulting in MSSV opening. Safety Injection Pumps are actuated at PZR low-level signal. Reactor trip happens early on high SG level signal. However, decay heat accumulates and heat transfer conditions on the primary side deteriorate following the loss of forced flow. Auxiliary Feedwater is actuated for the intact SG on low SG level signal to carry on heat removal function in the absence of the broken SG.

8. Uncertainty Quantification

The second piece of this work, and of best estimate plus uncertainty analyses, is uncertainty quantification. APR1400 simulations under SGTR with concurrent LOOP conditions are loosely coupled with the statistical tool DAKOTA to acquire the unknown range for important safety parameters and obtain a sizeable database to train ML models. This framework is shown in Figure 6. Uncertainty quantification is the process of generating the distribution of output parameters based on the distribution of input uncertain parameters. The first step, which is of vital importance, is to acquire knowledge of key uncertain input parameters that best describe the underlying phenomena of SGTR scenario. To complete this step, the phenomena identification and ranking table (PIRT) developed by Westinghouse on SGTR (Wilson et al., 1997), along with work by Ahn et al. (2008) on the state of PIRT development for Korean NPPs and work by Youn et al. (2017) on PIRT for Multiple-SGTR as a design extension condition is extensively utilized as key references. Each of the identified uncertain parameters is described by a probability distribution function which includes range, mean and standard deviation, as well as the type of distribution. Then, input uncertainty ranges are propagated into the thermal-hydraulic model using a simple Monte Carlo simulation. The number of samples is determined by Wilk's formula based on a chosen Wilk's order, a given probability distribution, and a confidence limit. This study adheres to the USNRC criteria of 95% confidence with 95% probability, and a Wilk's order of 5th as recommended by previous studies.[13] The results obtained from this procedure are thermal-hydraulic calculations under various perturbations of input conditions.



[Figure 6] Uncertainty Quantification framework

The quantity of data required for ML development cannot be determined with absolute certainty. For deep learning models, as used in this study, bigger data usually means better results.[12] The optimal dataset size should be determined, however, using a trial-and-error approach where model skill is evaluated against different data sizes since more data will drastically slow down the model. More crucially, outliers and edge situations must be included in the data provided because ML can only learn from examples and any cases outside this domain are not likely to be predicted by the model. In this sense, uncertainty quantification is important because it not only generates a significant amount of data (hundreds of thousands of examples or more), but also guarantees that the data is statistically representative of the key input uncertain parameters. By definition, the dataset obtained from uncertainty quantification is reasonably representative of the problem at hand which makes it a good fit for ML.

9. Machine Learning Model

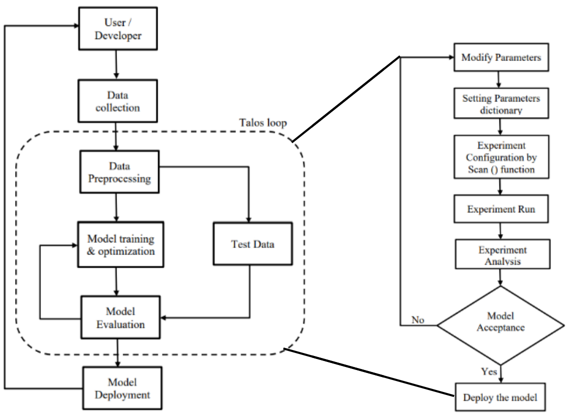
In this work, RNN-based structures LSTM, GRU, and hybrid CNN-LSTM are used to discern temporal patterns in datasets and make predictions on future trajectories of significant NPP safety parameters. The models learn by computing the difference between the predicted output and the actual output at each timestep to make appropriate adjustments in its structure to gradually arrive at the lowest possible error.

The following steps are taken to develop a robust ML model to predict NPP response in the event of an SGTR accident

1. Selection of input parameters.
   Input parameters with high correlations to key safety parameters of interest are selected to increase model performance.
2. Data preprocessing.
   This step includes data clearning, data normalization, data transformation and data splitting. 2D static data is transformed into 3-D data with an additional dimension of time.
3. Hyper-parameter tuning.
   Hyper-parameters are the building blocks of machine learning models. They determine how well the model can capture the relationships both between the input features and between input and output features. As such, hyper-parameter tuning is crucial to achieving good prediction accuracy. Many hyper-parameters can be tuned i.e. learning rate, number of hidden layers, number of nodes for each layer, activation function, number of epochs,

batch size, etc. This process can be very lengthy and tedious and so it was assisted by the open-source tool Talos, which test different combinations of hyper-parameters from a pre-defined search dictionary and return the corresponding evaluation metric of choice. The machine learning workflow and Talos loop are shown in Figure 7.

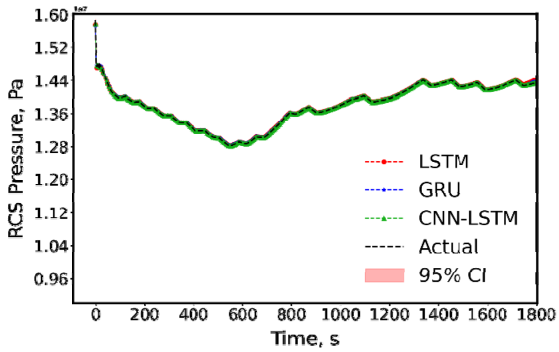
4. Model evaluation.
   The final step is to evaluate the model's ability to learn meaningful structures within the data and generalize what it has learned on fresh data to make accurate predictions.



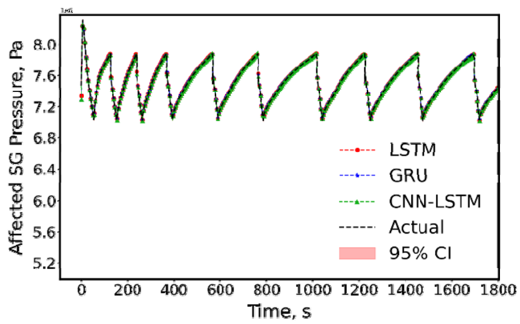
[Figure 7] Machine Learning workflow

10. Implementation Phase

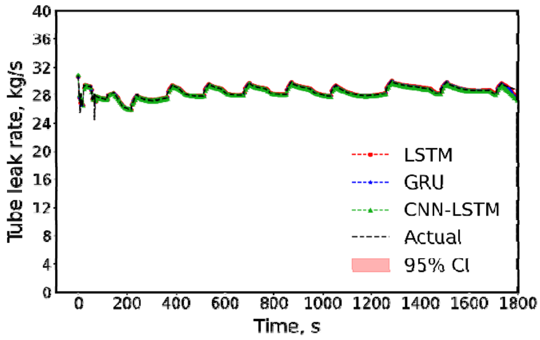
In this phase, each step described in the previous sections is carried out. Once the trained model has been validated, it can accurately and promptly predict any future system response given a defined set of input parameters. For example, future values of RCS pressure can be predicted by the model provided it has information on past values of RCS pressure and related parameters such as SG pressure, RCS temperature, and leakage flow. Results of prediction for four key safety parameters using various machine learning architectures are shown in Figure 8-11. Predictions are also compared with actual values from the physics-based model, showing high accuracy with little discrepancies across different models.



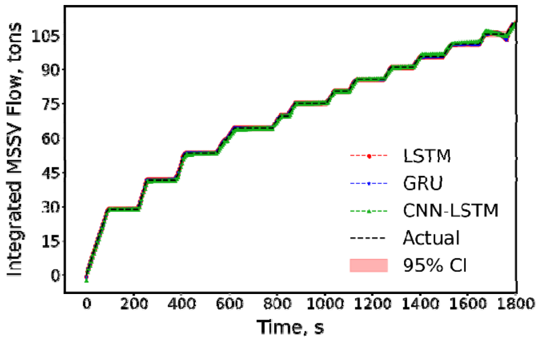
[Figure 8] Prediction for RCS pressure



[Figure 9] Prediction for affected SG pressure



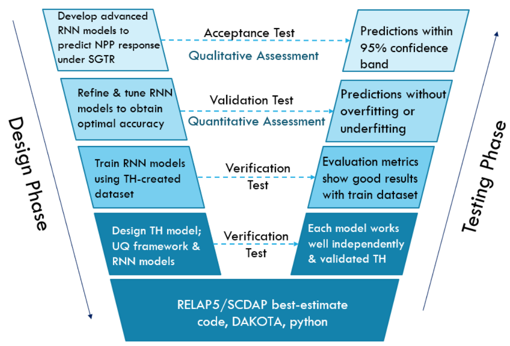
[Figure 10] Prediction for tube leakage rate



[Figure 11] Prediction for integrated MSSV flow

11. Verification and Validation Phase

A V-model (Figure 12) is used to delineate the project, control the quality, and reduce error throughout by dividing the work into four major stages each concluding with an applicable verification and validation test. This procedure also ensures that the project stays true to its stated goals.



[Figure 12] V-Diagram

At the most basic level, unit testing is done by running the core TH and ML models independently to make sure every component is working properly and matching reference results. Steady-state validation results, shown in Table 3, show reasonable agreement between the model and corresponding APR1400 DCD values.

<Table 3> Steady-state validation for APR1400

Parameter	DCD	Model
Initial core power level, MWt	4,062.66	4,062.66
Initial core inlet temperature, K	568.15	569.22
Initial pressurizer pressure,MPa (Primary pressure)	16.03	16.03
Initial core mass flow, kg/s	19,344	19,347
Maximum radial peaking factor	1.9786	1.9
Moderator temperature coefficient, 10−4 Δρ/oC	0.0	0.0
Doppler coefficient	Least negative	Least negative
CEA worth at trip, % Δρ	−8.0	−8.0

Integration testing is done by combining the models then training and refining the ML models on the dataset generated by the previous TH methodology. Moving up one level, system testing refers to model capability verification by making predictions on the unseen test dataset. The model's effectiveness is evaluated for overfitting, underfitting, which are common problems in training ML models. The model's capacity to generalize learning patterns on new data is also an important evaluation point. Any bugs and lingering problems with the model should be resolved by this stage. The model's capability in an uncontrolled environment is verified during the final test, known as acceptance testing. RNN model evaluation metrics used in this study include mean squared error (MSE), mean absolute error (MAE), root mean square error (RMSE), and coefficient of determination (R2). These metrics are defined as follows:

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(y_{predicted} - y_{actual})^2$$

$$MAE = \frac{\sum_{i=1}^{n}|y_{predicted} - y_{actual}|}{n}$$

$$SE = \sqrt{\frac{\sum_{i=1}^{n}(y_{predicted} - y_{actual})^2}{n}}$$

$$R^2 = 1 - \frac{\sum(y_{actual} - y_{predicted})^2}{\sum(y_{actual} - y_{mean})^2}$$

High-fidelity models are expressed by low errors approaching 0 and high R^2 approaching 1 (Table 4).

<Table 4> ML model performance metrics

Parameter	ML Models	MSE	RMSE	MAE	R^2
RCS pressure	LSTM GRU CNN-LSTM	0.0048 0.0049 0.0053	0.0694 0.0700 0.0730	0.0076 0.0119 0.0058	0.9994 0.9993 0.9946
Tube leakage rate	LSTM GRU CNN-LSTM	0.0177 0.0173 0.0174	0.1330 0.1315 0.1318	0.0166 0.0155 0.0132	0.9978 0.9978 0.9826
Affected SG pressure	LSTM GRU CNN-LSTM	0.0072 0.0074 0.0070	0.0851 0.0857 0.0837	0.0190 0.0146 0.0174	0.9981 0.9980 0.9929
Integral MSSV flow	LSTM GRU CNN-LSTM	0.0088 0.0089 0.0091	0.0948 0.0943 0.0954	0.0081 0.0126 0.0145	0.9988 0.9989 0.9908

12. Conclusion

A Systems Engineering approach was adopted to systematically facilitate and monitor the development of robust ML models to forecast key safety parameters under SGTR accident conditions. A series of verification and validation steps are carried out to ascertain that the requirements with established success criteria are met for each stage. It is hoped that this project can provide a missing piece to the expanding puzzle of ML applications in accident management and create a knowledge base for the development of a more comprehensive guidance tool under more severe accident conditions.

The developed models demonstrated the ability to make predictions for SGTR system behavior with a high degree of accuracy and precision at a much lower computational cost than conventional physics-based models. Another significant benefit is the ability of machine learning models to continuously adapt and adjust themselves based on fresh incoming data. This characteristic makes them suitable as real-time tools that collect and interpret data from sensors at the moment of an accident to provide timely and useful assistance.

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