THE OHIO STATE UNIVERSITY

Use of Machine Learning Techniques to Reduce the Computational Effort in Dynamic Probabilistic Risk Assessment

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Objective

What is the most challenging part of the DPRA methods?

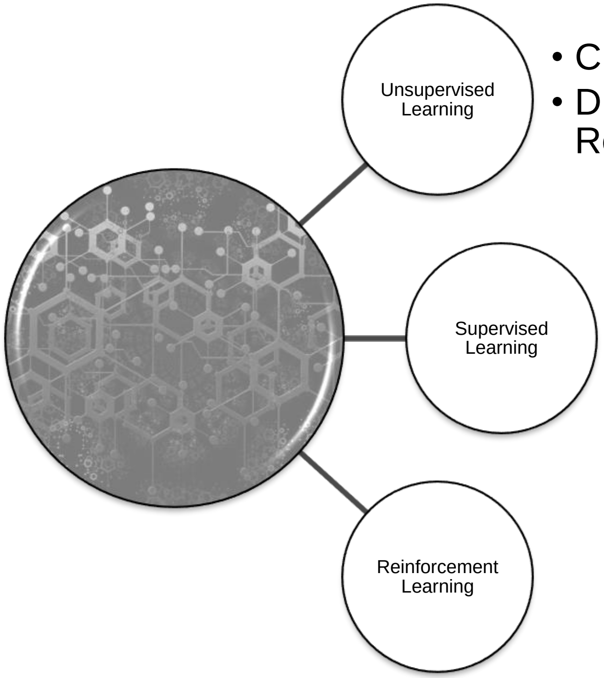
How can we speed up the DPRA process?

- Advantages of dynamic probabilistic risk assessment (DPRA) [1]:
  - Time-dependent results can be obtained
  - Many accident scenarios can be studied
  - In particular, complex structures of new reactor designs can be analyzed more easily than classical methods.
- Challenges of DPRA:
  - The computational cost is very high
  - Evaluate the results can take a long time
  - Number of scenarios that can be examined is limited.

ML methods can be replaced with DPRA tools?

How can we integrate ML methods into the DPRA?

Machine Learning Overview



- Clustering
- Dimensionality Reduction

- Classification
- Regression

Figure 1. Types of Machine Learning

- Advantages of Machine Learning (ML) [2]:
  - Large data sets can be analyzed effectively,
  - Total simulation time can be greatly reduced,
  - Performs standardized, repetitive actions
  - Continuous model improvement

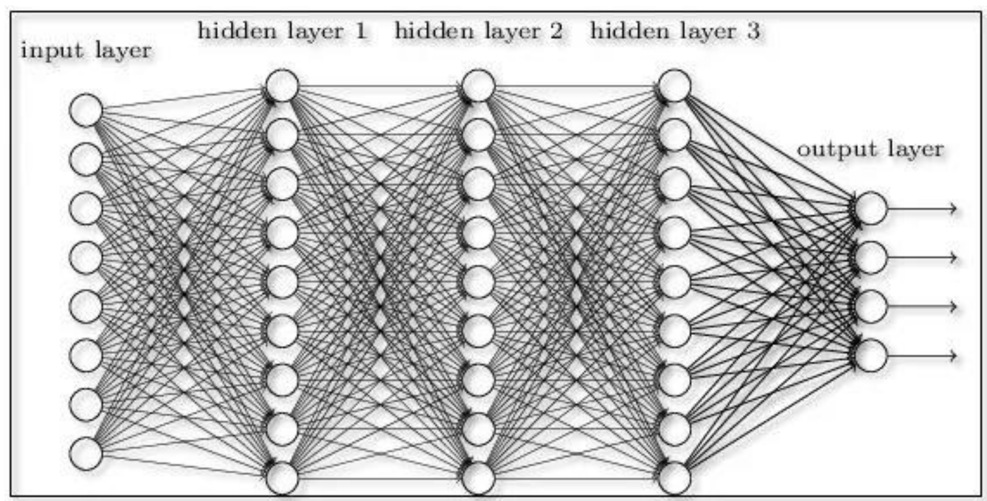


Figure 2. Deep Neural Network Architecture [3]

Methodology – Recurrent Neural Networks (RNN)

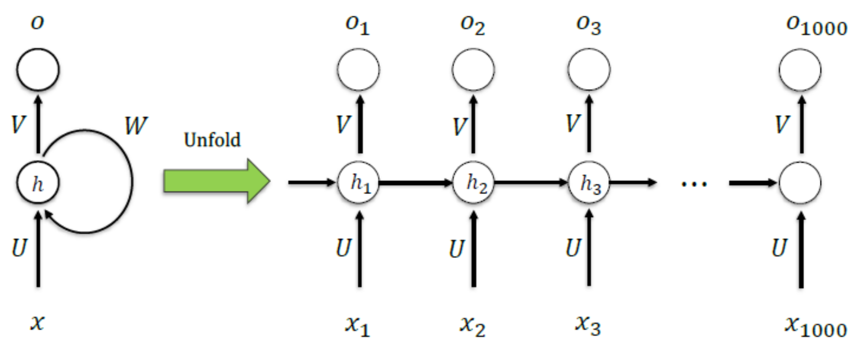


Figure 3. RNNs Architecture [4]

- The main advantage and necessity of using RNNs is feedback connection that plays vital role in capturing the context information
- RNNs have “memory” which remembers all information incorporated into the model
- Training an RNN is a difficult task with gradient exploding and vanishing problems [4].

- ➢ Long Short Term Memory (LSTM) a unique kind of RNN, capable of learning long-time period dependencies,
- ➢ LSTM is well-suited to classify, process and predict time series.
- ➢ It is solution to vanishing and exploding gradient issues [5].

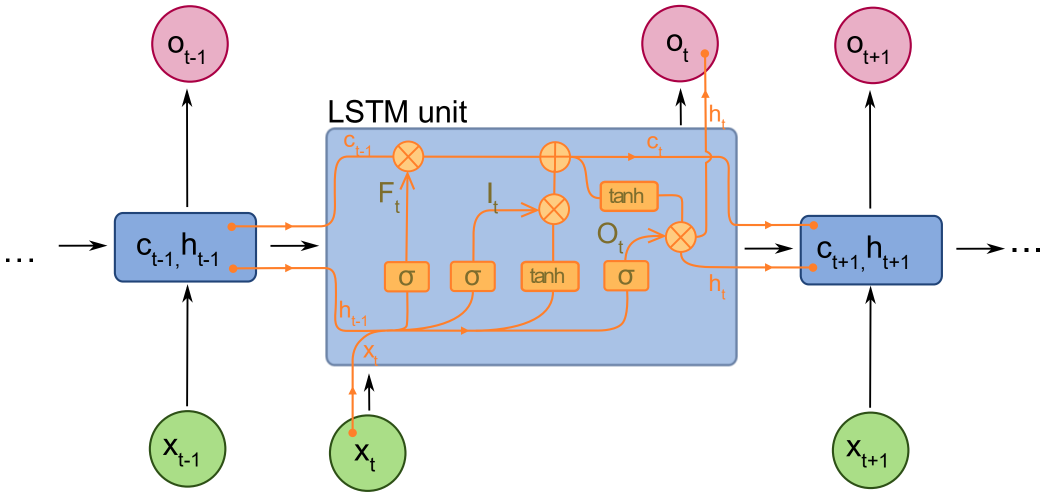
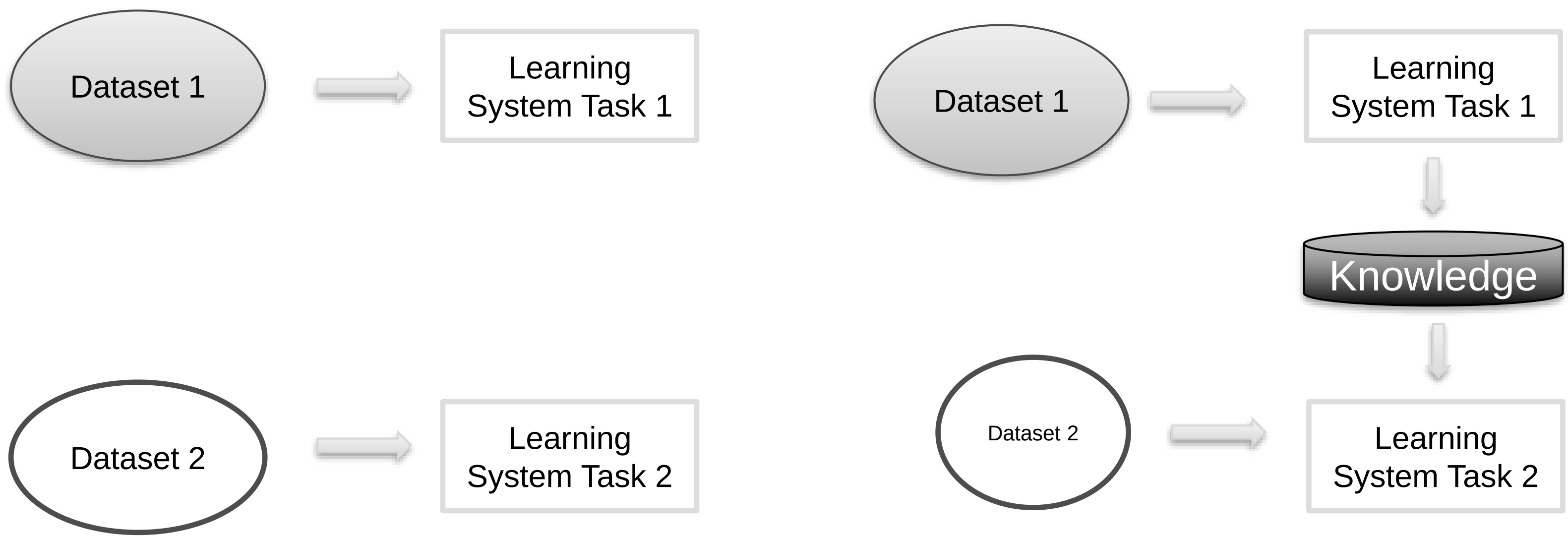


Figure 4. LSTMs Architecture [5]

Methodology – Transfer Learning

Traditional ML vs. Transfer Learning

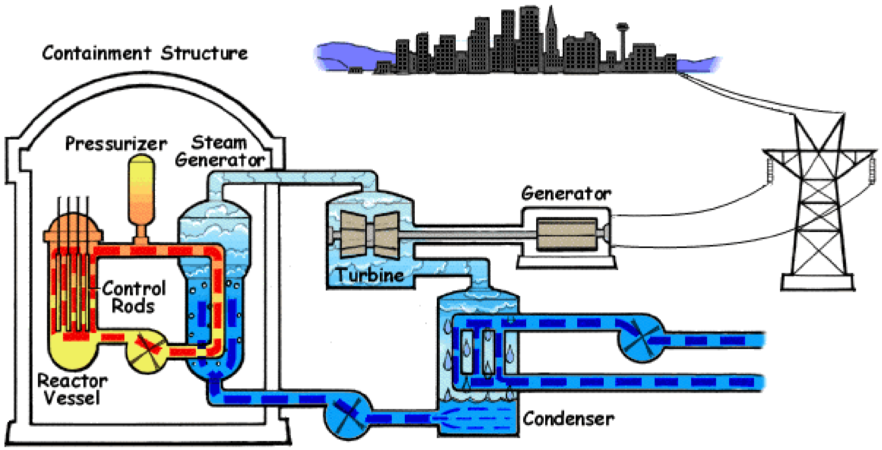


- Isolated, single task learning
- Knowledge is not retained or accumulated.

- Learning new tasks relies on previously learned task.
- Learning process can be faster, more accurate and/or need less training data.

Analysis – System Overview

- Typical 4-loop Pressurized Water Reactor (PWR)
- Initiating event: Station Blackout Accident (SBO)
- Possible scenarios following the initiating event were generated using RAVEN [6] and RELAP5-3D [7]
- RAVEN was used as the driver for the 4-loop PWR simulations



Source NRC

Table 1. Major RELAP5-3D Modeling Parameters [4]

Parameter	Unit	Value
Core Thermal Power	MWth	3850
Total Primary Volume	ft^3	14300
Secondary Volume	ft^3	30500
Steam Generators PORV Setup Point	psia	1235
Pressurizer PORV Opening Setup Point	psia	2350
Pressurizer PORV Closing Setup Point	psia	2330
PORV: Pilot-operated Relief Valve		

Analysis – Dataset Overview

- Scenario datasets were generated from selected initiating events and branching conditions.
- Total number of RELAP5-3D SBO simulations is 9,587.
- RELAP5-3 branching conditions (BCs) (total of 9) included power recovery, steam generator safety valve reclosing failure, reactor coolant pump seals integrity and emergency power duration [8].

Table 2. Example BCs and Data for RELAP5-3D SBO Simulations [8]

BC	Parameter	Distribution	From	To
Offsite Power Recovery	Recovery Time	Uniform	5 hours	10 hours
Diesel Generator Power Recovery	Recovery Time	Uniform	1 hour	10 hours
Auxiliary Feedwater (AFW) System	AFW Power Off	Uniform	1 second	4 hours
Primary system safety valve reclosing failure	Valve Stuck Open Time	Uniform	1 second	10 hours
	Valve Stuck Open Cycle	Uniform	1	20
Reactor coolant pump (RCP) Seal LOCA	Break Opening Time	Uniform	30 minutes	10 hours
	Break Size	Uniform	0.005 ft2	0.12 ft2
RCP Controlled Bleed-off	Isolation Time	Uniform	5 minutes	5 hours
Secondary side depressurization procedures	Depressurization Procedure Starting Time	Uniform	0 s	10 hours
	Cooling Slope	Uniform	0.01 K/s	0.02 K/s

Analysis – Dataset Pre-Processing

- Each branch of a scenario contains a large number of state variables, and the resulting data are high-dimensional in both state variables and time.
- To describe the temporal behavior of all system state variables (e.g., pressure and temperature), we represent each scenario $\boldsymbol{x}_i$ (i=1,…,I) by M state variables $\boldsymbol{x}i$ (m=1,…,M) and time length T as the $M*L$ matrix:

$$\boldsymbol{x}_i = \begin{bmatrix} x_{i1}(t_1) & \cdots & x_{i1}(t_L) \\ \vdots & \ddots & \vdots \\ x_{iM}(t_1) & \cdots & x_{iM}(t_L) \end{bmatrix}$$

$$\overline{\boldsymbol{x}}_{im} = \frac{x_{im} - min(x_{im})}{max(x_{im}) - min(x_{im})}$$

- Another issue that arises when dealing with nuclear transients is due to different scales of the variables used.
- Hence, each variable in scenario needs to be normalized into the range of 0 and 1.

Analysis – Implementation Details and Training Process

- Multivariate LSTM time series prediction (many-to-many),
- Total number of input parameters: 19
- Total number of predicted output parameters: 3

Table 3. List of input parameters

Parameters
Primary coolant inventory
Steam Generator (SG) coolant inventory – SG1, SG2, SG3, SG4
Cumulative volumetric follow rate from small RCP LOCA break
Subcooling level in the cold leg (CL) – CL1, CL2, CL3
Upper Plenum Liquid Temperature
Pressurizer Pressure
Pressurizer Level
Core Inlet Temperature
Auxiliary Feedwater Tank inventory – FW1, FW2, FW3, FW4
Total amount of generated hydrogen
Availability of the power from the grid

Table 4. List of predicted output parameters

Parameter
Peak Clad Temperature
Core Outlet Temperature
Subcooling level in the cold leg – CL4

Analysis – Implementation Details and Training Process

Table 5. Training Hyperparameters

Parameter	Value
Number of layers	3
Hidden size	100
Learning rate	0.01
Number of epochs	60
Batch size	100

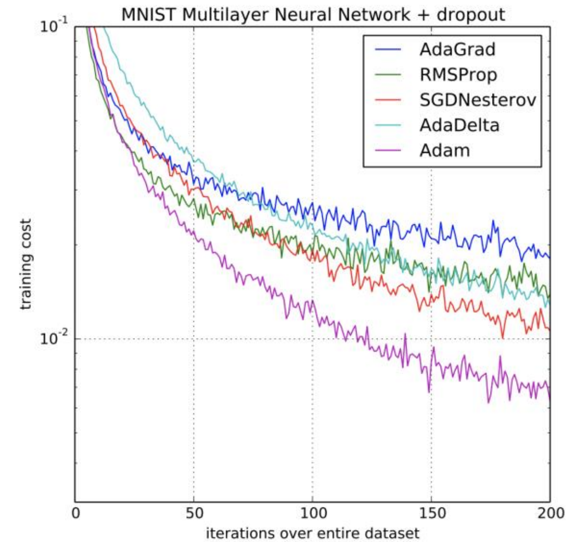


Figure 5. Comparison of Adam to Other Optimization Algorithms Training a Multilayer Perceptron [9]

- LSTM network is implemented using open-source AI framework PyTorch [10] which contains various architectures of neural networks, and which can be easily utilized with input and output data.
- The training process is completed on a computer with NVIDIA GTX1080 GPU.
- Loss function – Mean Squared Error (MSE)
- Optimizer – Adam

$$MSE = \frac{1}{n} \Sigma \underbrace{\left(y - \widehat{y} \right)^2}_{\text{The square of the difference between actual and predicted}}$$

n: number of samples

Analysis – Implementation Details and Training Process

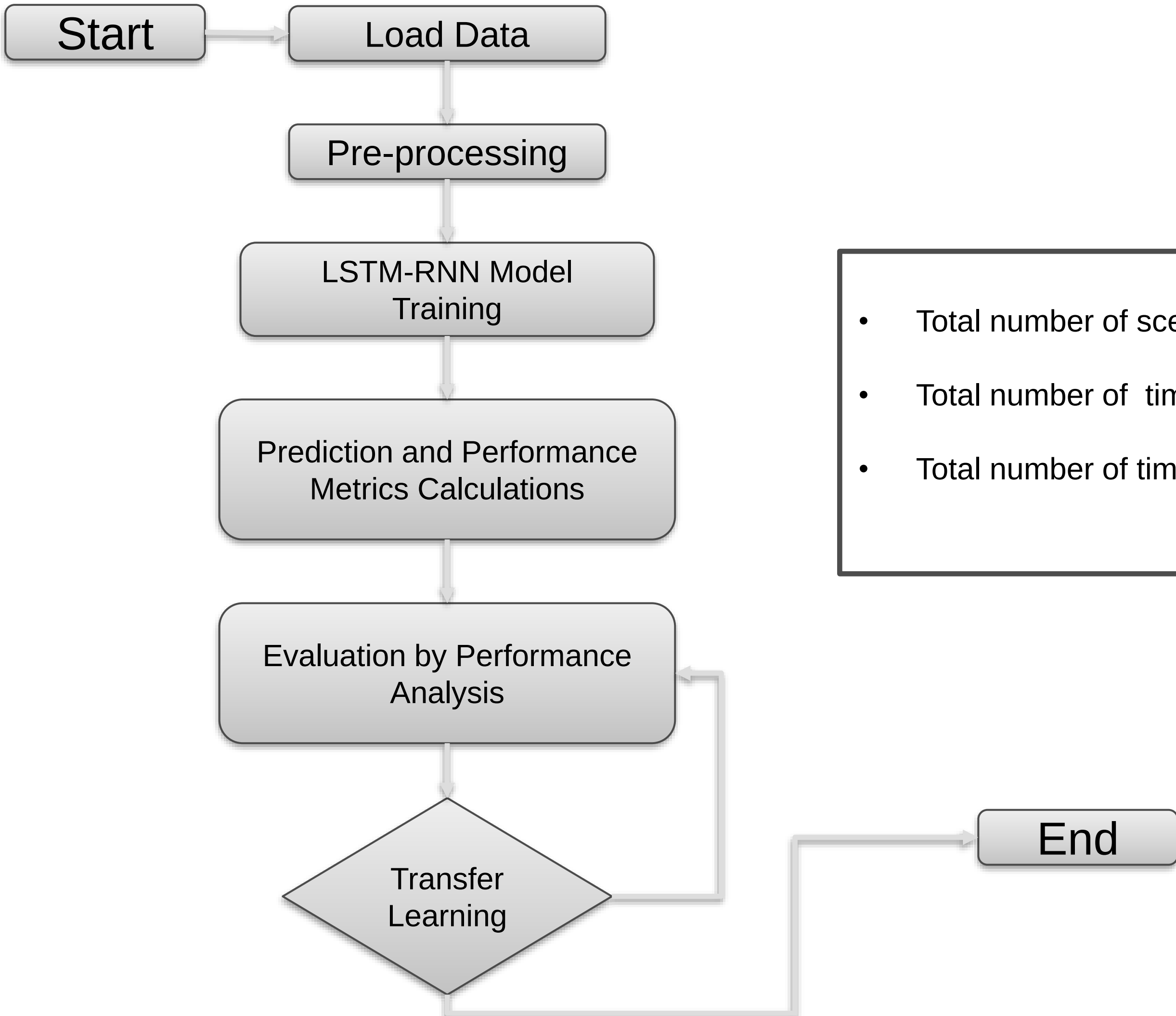


Figure 6. Flowchart of LSTM training with Transfer Learning

- Total number of scenarios: 9,587
- Total number of time steps in used training: 800 (80%)
- Total number of time steps in used evaluation: 200 (20%)

Results

- The loss can be observed to converge quickly.
- Results show that LSTM is correctly trained with complex nuclear reactor data.

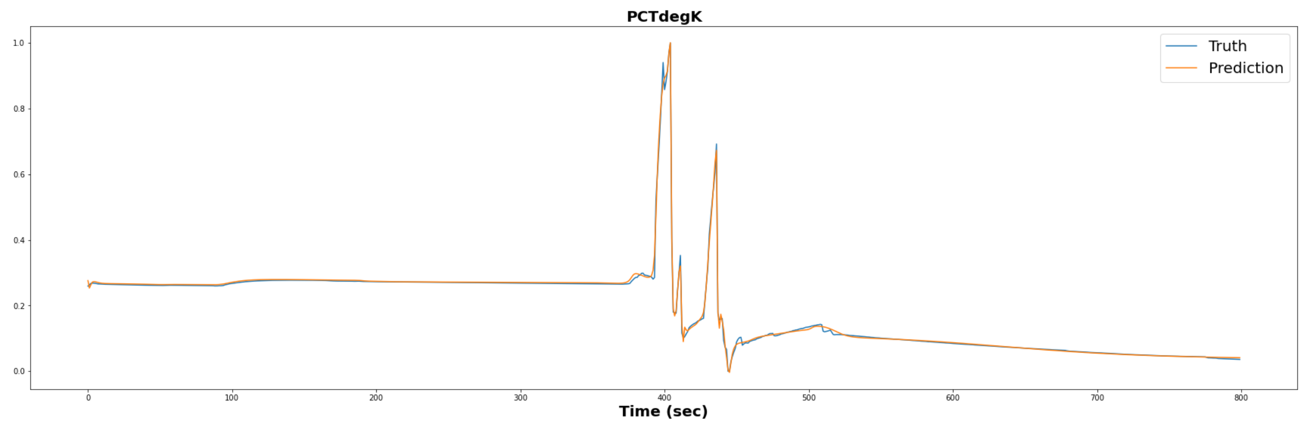


Figure 7. Training results for Peak Clad Temperature

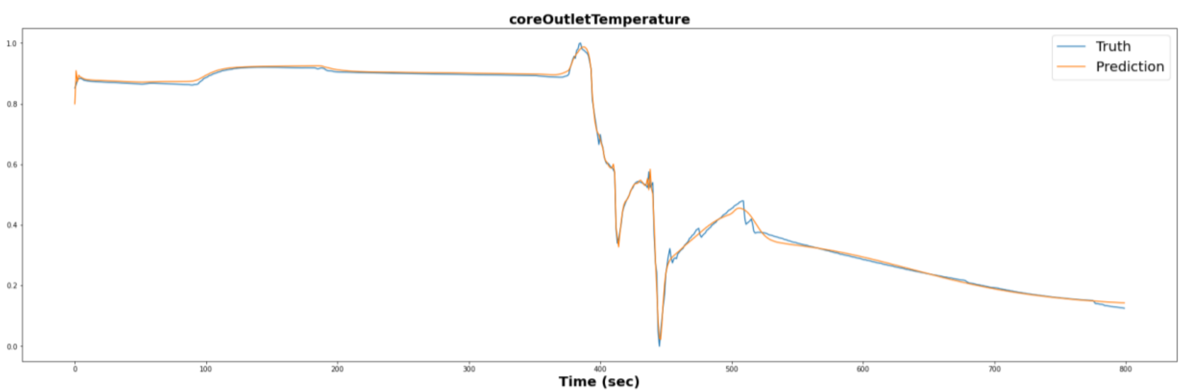


Figure 8. Training results for Core Outlet Temperature

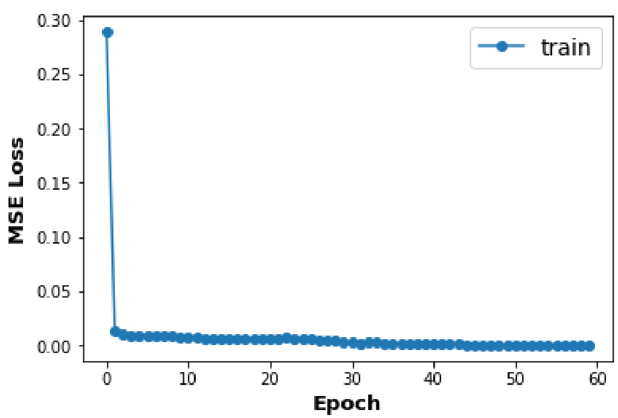
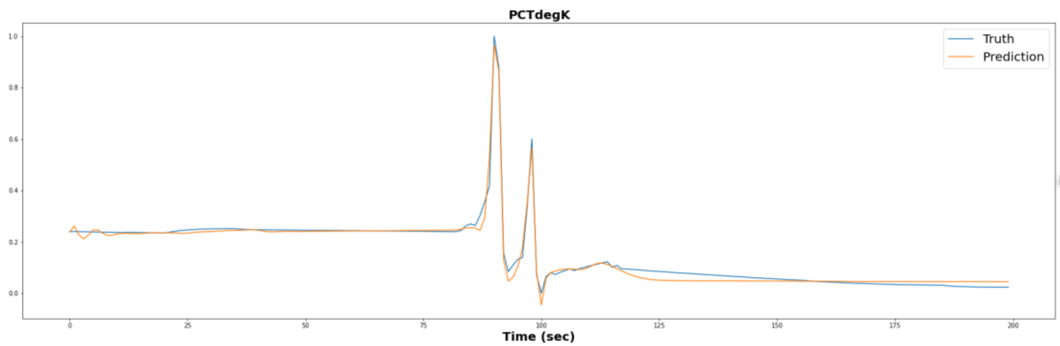
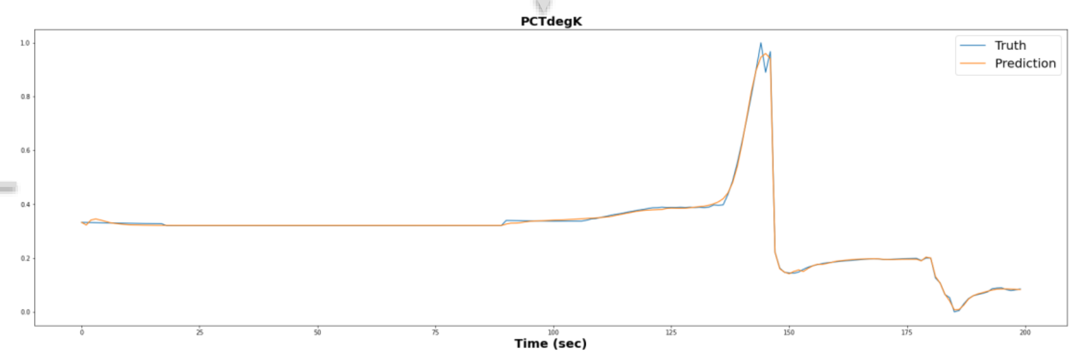


Figure 9. Training loss

Results

- Benefit of transfer learning application can be observed on different scenario progressions.





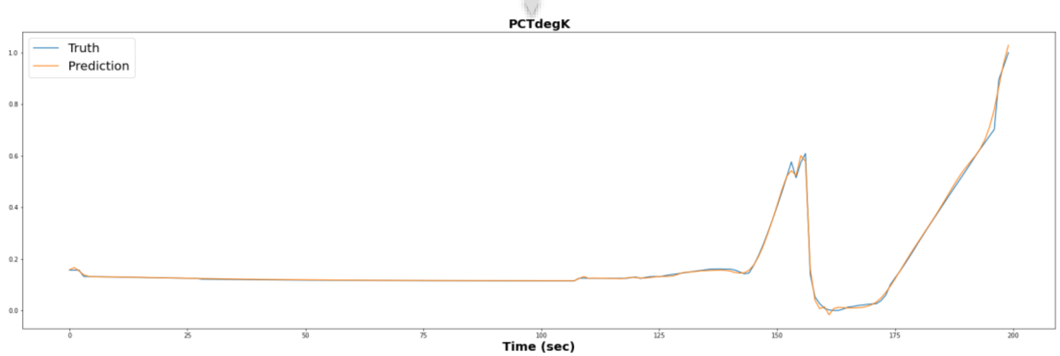


Figure 9. Effect of transfer learning application on the results

Conclusion and Future Work

- This study is aimed at using DPRA data sets for a typical PWR to train the LSTM-RNN model to make predictions of possible reactor behaviour under accident conditions as the accident evolves.
- Results show that the LSTM method is suitable for nuclear reactor data.
- Transfer learning application has provided a great benefit in obtaining more accurate results with less computational time.
- When using the data from different reactors, it is necessary to pay attention to the compatibility of the input and predicted parameters.

- In order to make the most accurate prediction of nuclear reactor behavior, other machine learning methods will be used and results compared.
- The resulting method will be applied for dynamic probability safety analysis of multi-unit small modular reactors.

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Question and Answers