



#### Demonstrating Autonomous Architectures for Microreactors Under Prototypic Conditions in PUR-1

2024 Microreactor Program Review

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### Team Info

#### Purdue

- Stylianos Chatzidakis (Assistant Professor and Associate Reactor Director, SRO)
- True Miller (Reactor supervisor, SRO)
- Brian Jowers (Electronics/I&C reactor staff, RO)
- V. Theos, Z. Dahm, K. Vasili, K. Gkouliaras, W. Richards (Grad students)

#### UNM

- Mohamed El-Genk (Professor)
- Timothy Schriener (Research Assistant Professor)

#### Collaborators

- Robert Ammon (Curtiss-Wright)
- Rick Vilim (ANL)
- TPOC: Ben Baker (INL)





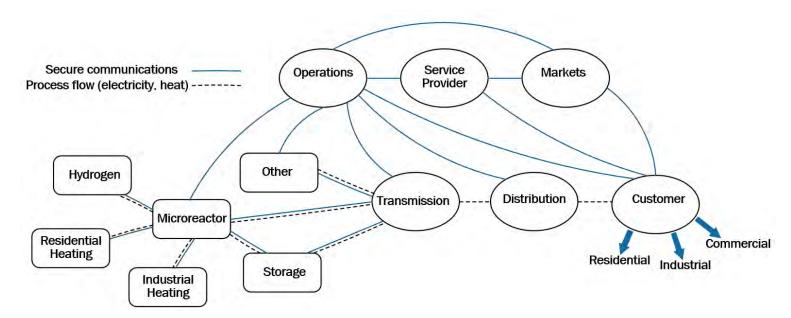








### New technologies...new challenges



New reactor concepts => Significantly different requirements than existing fuel cycle facilities Digitalization => New architectures and new vulnerabilities

New technologies => Quantum computing Adversaries now have access to new tools with unprecedent capabilities





## Goals & Objectives

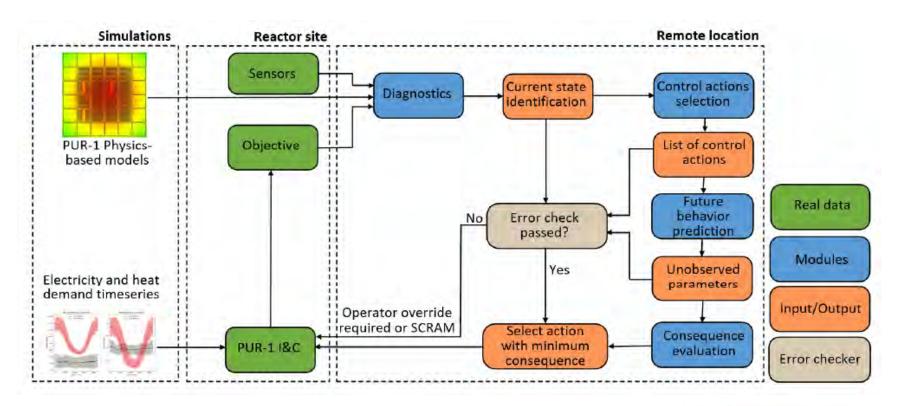
**Goal:** Experimentally validate semi-autonomous control and demonstrate its use in PUR-1 and VSLIMM.

#### **Objectives:**

- 1. Develop a modular digital twin platform with various levels of automation using a remote workstation with AI/ML algorithms
- 2. Train AI/ML using physics-based microreactor models and realtime digital operation data collected from PUR-1
- 3. Perform testing and evaluate performance



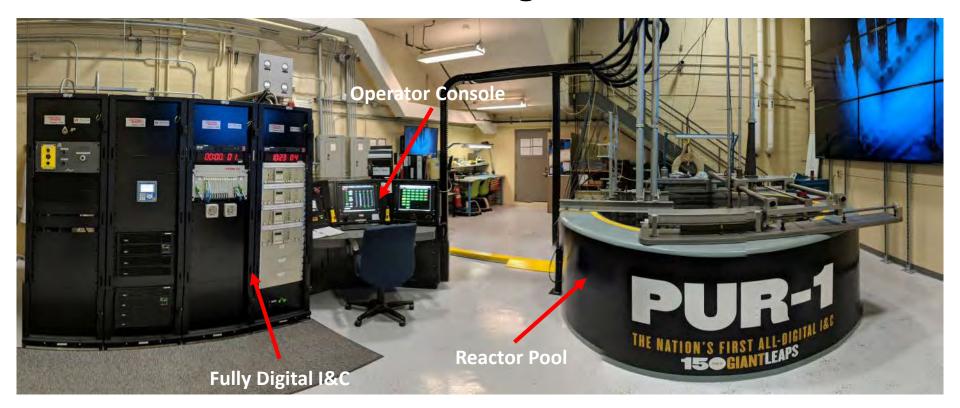
### Semi-autonomous Architecture







## Introducing PUR-1







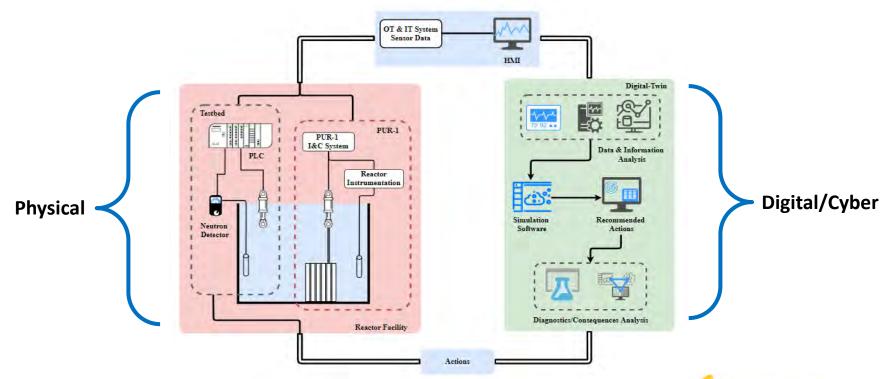
### Before and after...



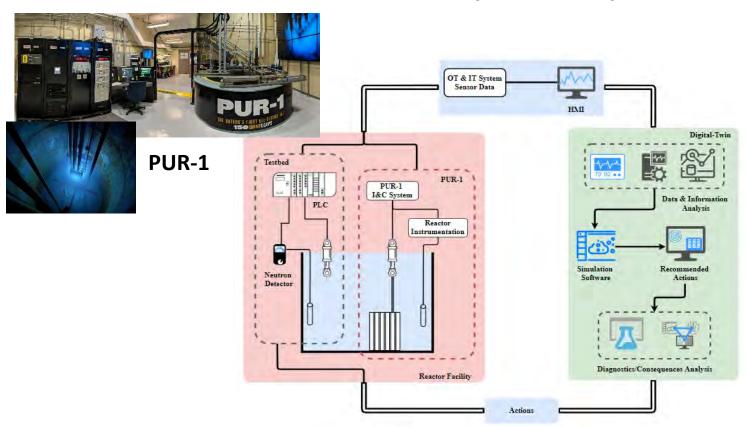
2019 - present

1960 - 2017



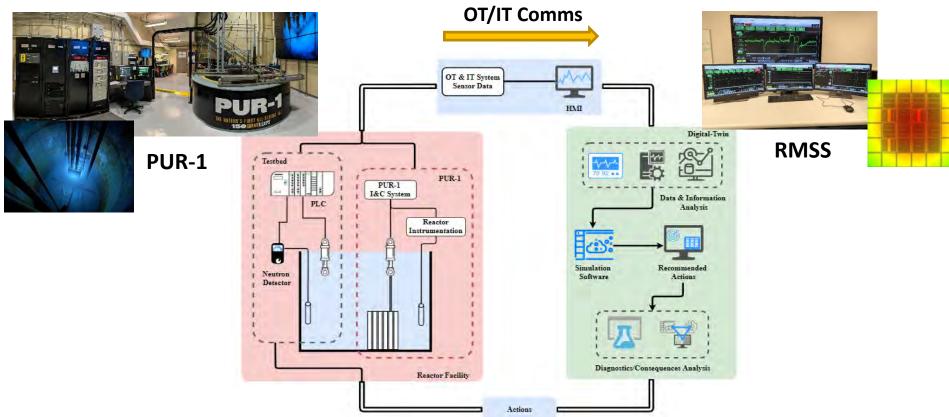




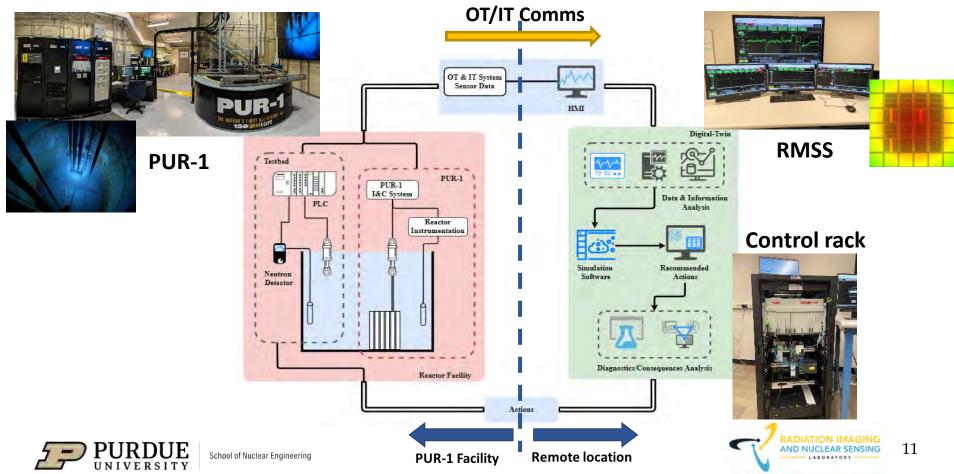


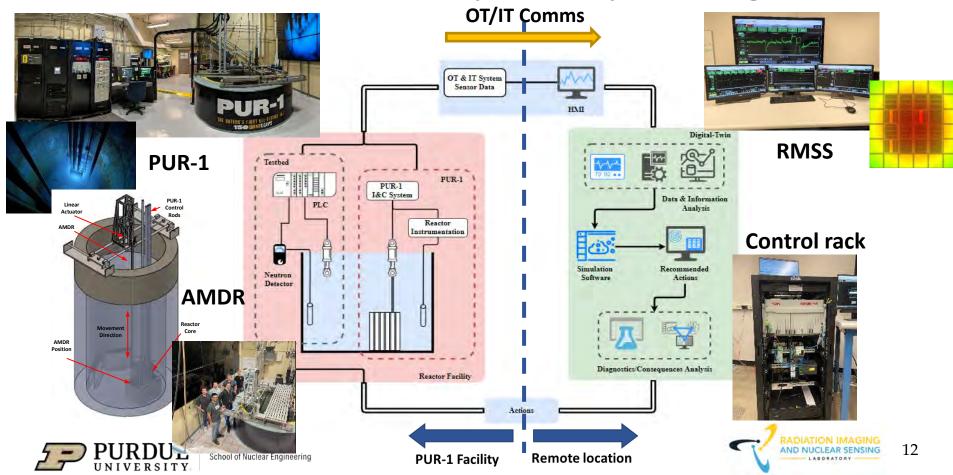












Digital/Cyber Remote Station

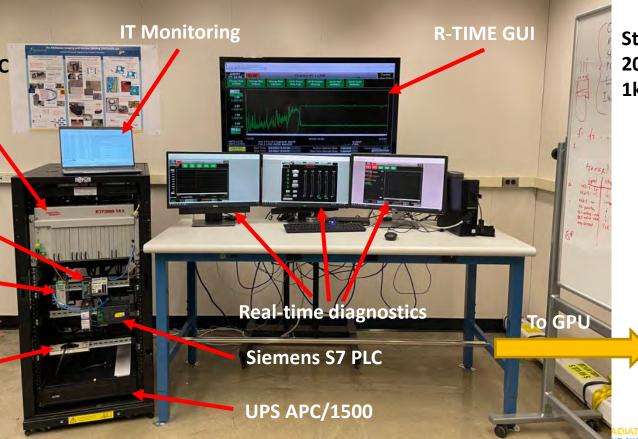
RTP 3000 TAS N+
Nuclear grade PLC
16 CH AI/AO
32 CH DI/DO

Field
Programmable
Gate Array

Power distribution unit

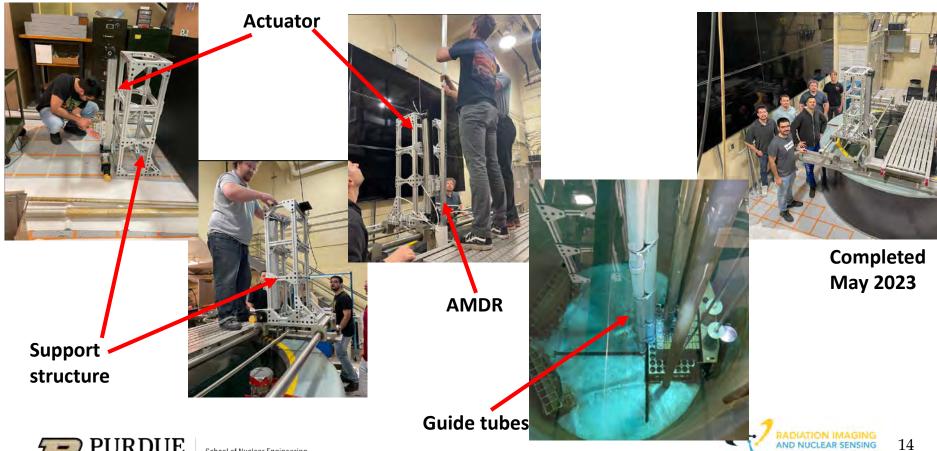
**Actuator control** 

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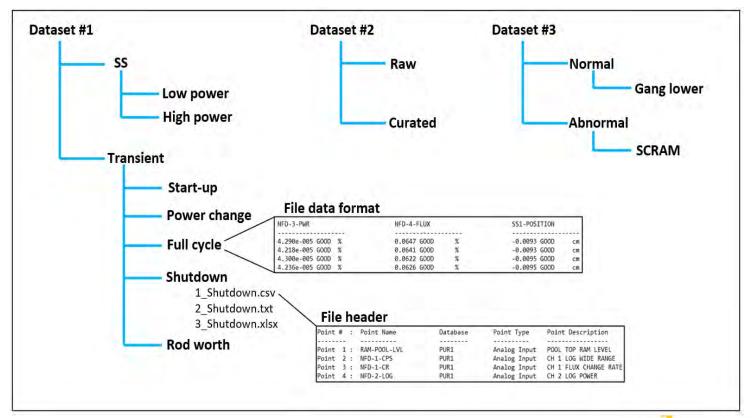


Stats: 2000 parameters 1kHz sampling

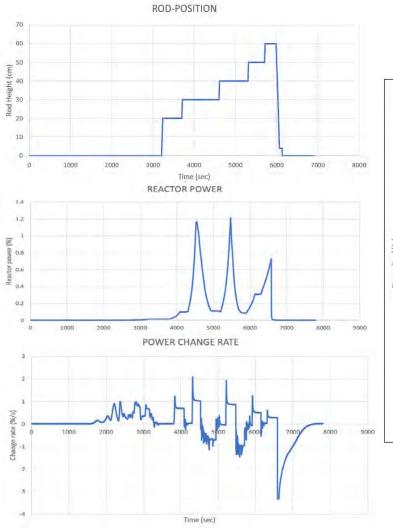
# Installing and Testing AMDR

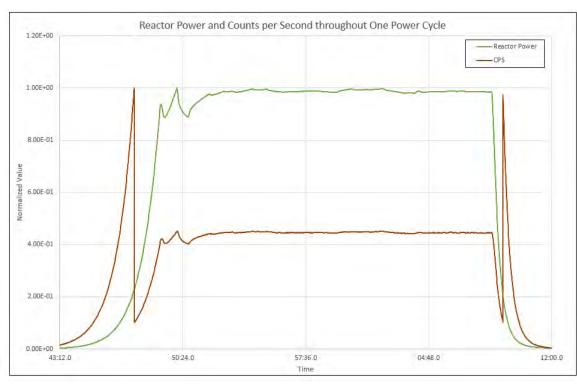


## Datasets for Benchmarking



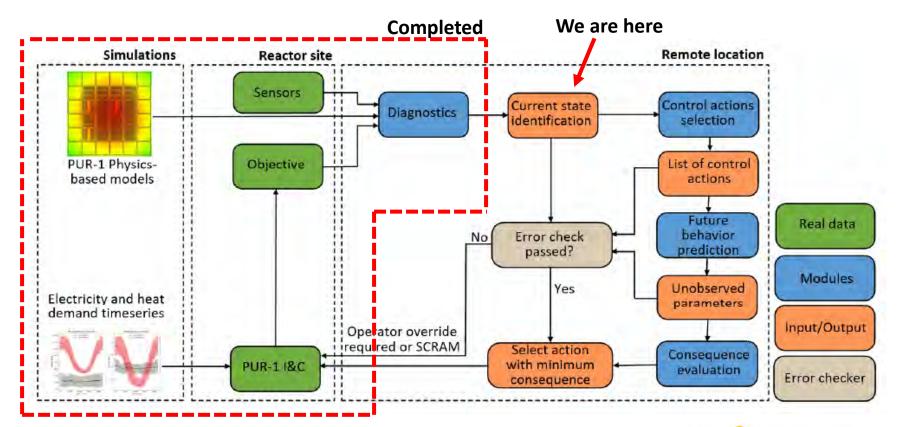








### Semi-autonomous Architecture







### **Reactor State Identification**

The following classes were defined for PUR-1 operational data

class	Instances (s)	Feature number
reactor startup	967 s	67 features
steady state 20%	876 s	67 features
steady state 50%	443 s	67 features
steady state 70%	145 s	67 features
steady state 90%	405 s	67 features
scrams	400 s	67 features
Gang lower	400 s	67 features





### Reactor State Identification

- The data were checked for Null (limited Null values were found)
- ➤ The data were checked for outliers (No significant variations from min max values)
- Check for Noise (methodology has been defined and published – need to be refined to handle multidimensional data)
- The data were Normalized (0-1)
- ➤ The data were split to 80%-20% (training/testing)
- Various ML approaches were investigated
- Various metrics were extracted (precision, recall, f1-score, accuracy, confusion matrix)

Necessary steps since we are dealing with real, operational data



### Training

Do we have to use NN for this problem or classic ML and less complicated approaches suffice?

- > SVM
- Random Forest
- Decision Trees
- ➤ Logistic Regression
- Naive Bayes

#### **MULTICLASS CLASSIFICATION**

- 7 classes
- 67 features each

Vs Neural Network

MULTICLASS CLASSIFICATION

• TBD



#### Results

- Other algorithms have similar results
- Naïve Bayes yields a small number of misclassifications

```
Predicting the Test set results for Decision Tree:
Predicting the Test set results:
confusion matrix:
[[194  0  0  0  0  0  0]
[  0  175  0  0  0  0  0]
[  0  0  88  0  0  0  0]
[  0  0  0  29  0  0  0]
[  0  0  0  0  81  0  0]
[  0  0  1  0  0  79  0]
[  0  0  0  0  0  0  80]]
```

```
Predicting the Test set results for Random Forest:
Predicting the Test set results:
 onfusion matrix:
Predicting the Test set results for Naive Bayes
Predicting the Test set results:
confusion matrix:
```



### Conclusions

- While NN are powerful tools for classification and regression tasks, other approaches can also be effective
- For classification tasks, RF, DT, LG, SVM and NB yield competitive results
- Slight misclassifications with NB
- > For regression tasks RF, DT outperform NN
- Classic approaches handle effectively the non-linearity in the data
- > Classic approaches need minimum amount of data
- ➤ NN results will possibly improve with further exploring the optimal architecture and increasing the amount of training data



### **Future Work**

- Dimensionality reduction techniques
- > PCA for reducing the amount of training features
- For classification further examining an optimal architecture
- Deep learning techniques
- Control rod predictions in different power levels
- Investigate the capability of predicting all control rods used (ss1, ss2, rr) instead of only 1 (rr)

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