

Optimal Sparse Sensing and Sparse Learning for Nuclear Digital Twins

Idaho National Laboratory, University of Washington, Seattle

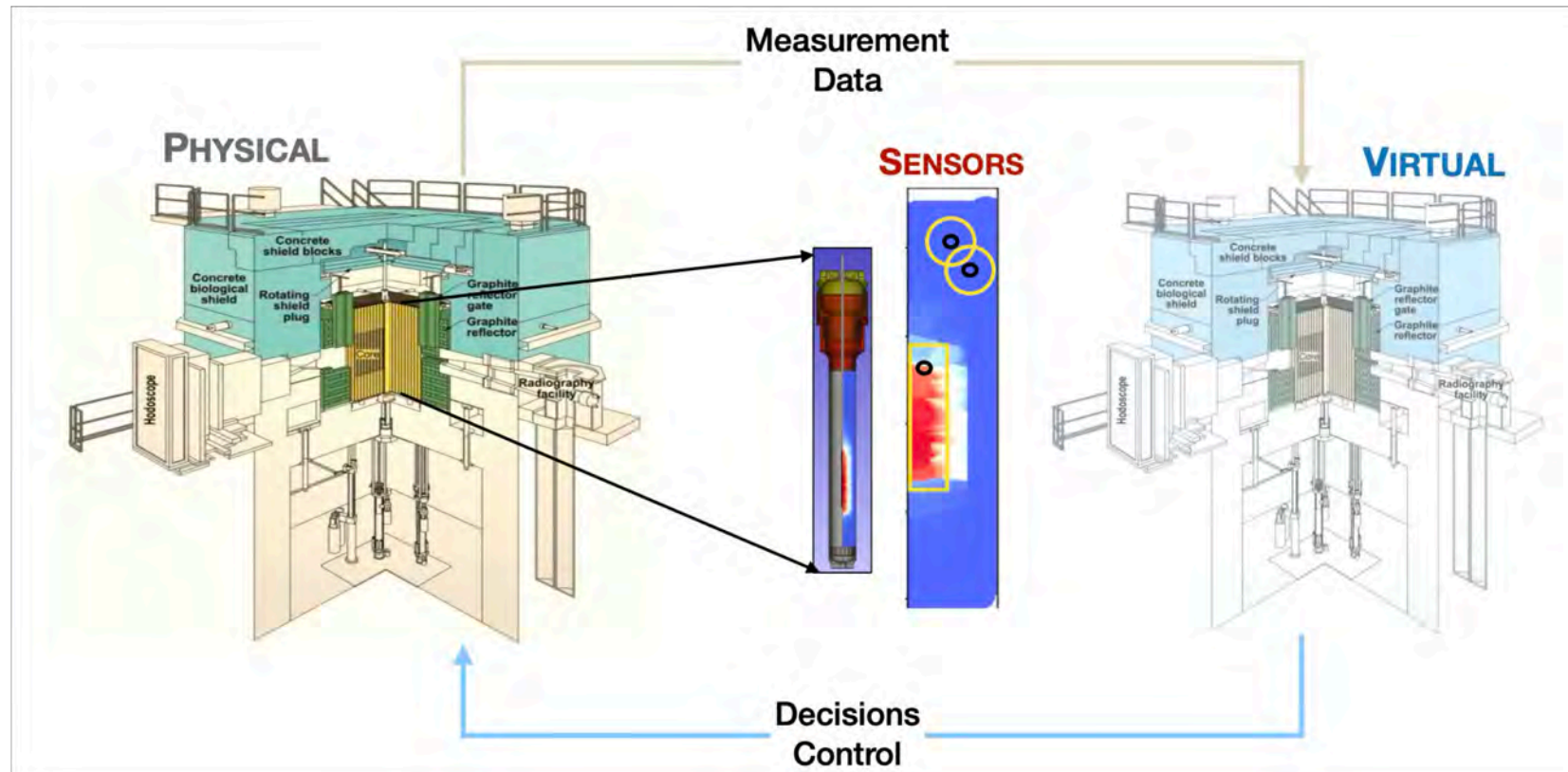
Presenter: Niharika Karnik, Ph.D., Postdoc C-230 Plant Optimization

PI: Mohammad Abdo, Ph.D., Distinguished Technical R&D staff Scientist C-540 Autonomous Engineering



Project Overview

- Enable sparse sensing and learning in nuclear digital twins through reconstruction of reactor core flow fields, using optimal sensor placement with **spatial constraints**.



Project Team



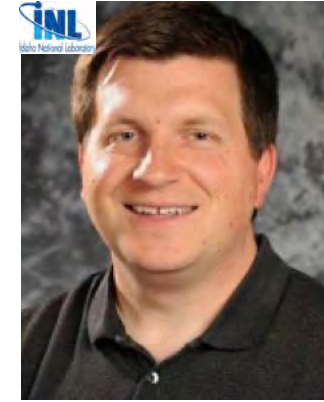
Mohammad G Abdo : PI



Patrick Calderoni : Co-PI



Joshua Cogliati : Co-PI



Richard Skifton



Carlos Perez



JunSoo Yoo



Krithika Manohar : Co-PI



Steven L. Brunton : Co-PI



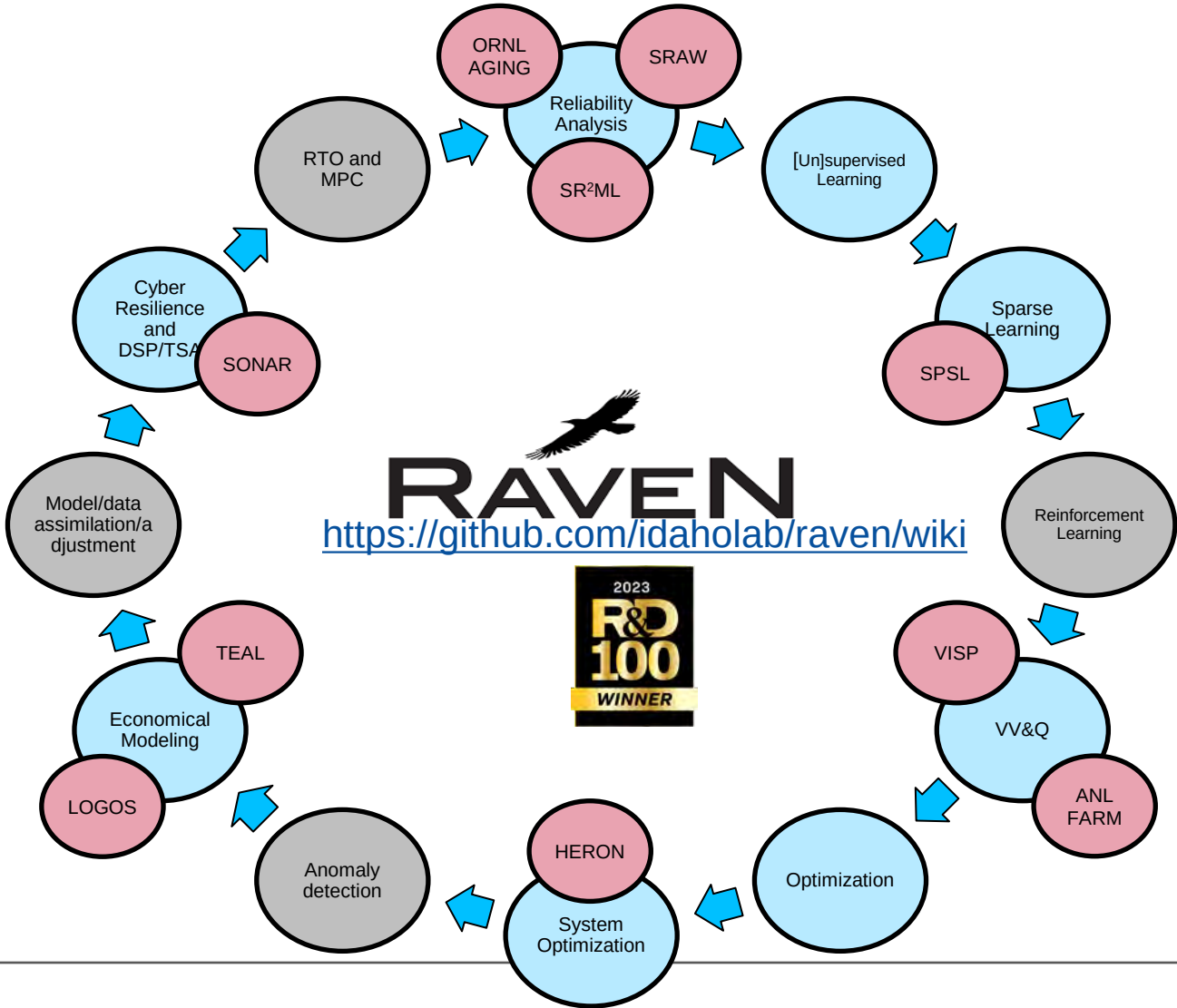
Niharika Karnik : Ph.D. Student

What is a Digital Twin?

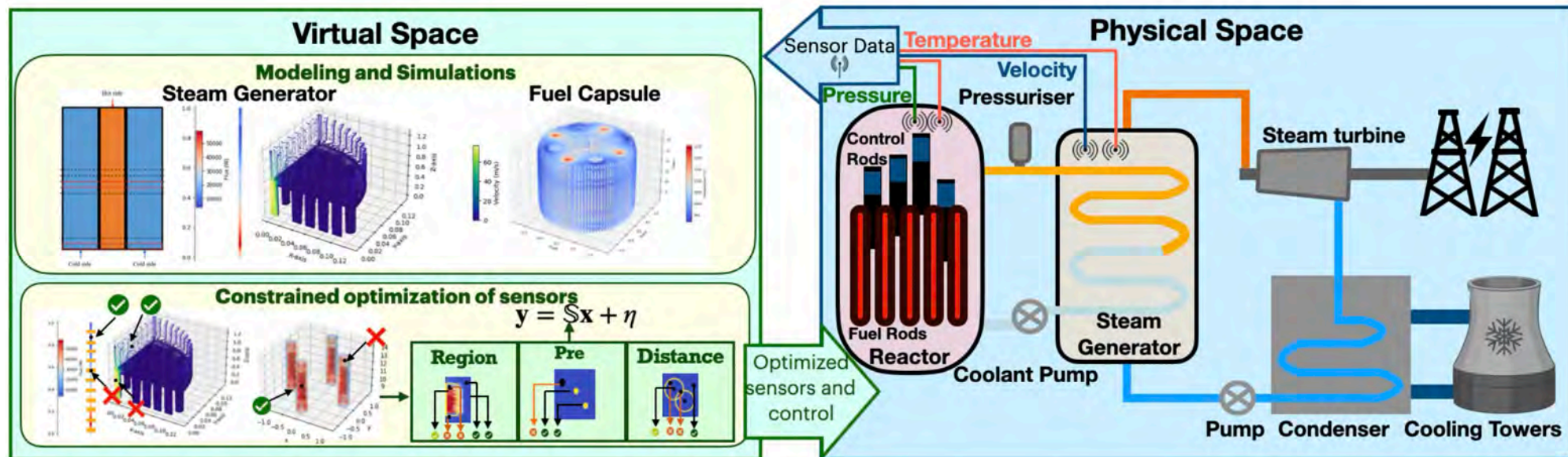


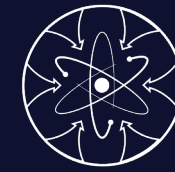
- A digitized replica of a physical component, system, or process rendering its whole lifecycle utilizing connectivity to real-time sensor data alongside deep analytics (ML?DL/AI).

DT Requirements



- Reconstruction with uncertainty estimation of fields of interest from sparse noisy sensor measurements in spatially constrained assets.
- Customers: Every entity that uses instrumentation (power plants, utilities, vendors, testing regs, universities running experimental facilities, TREAT, Microreactors, etc.)

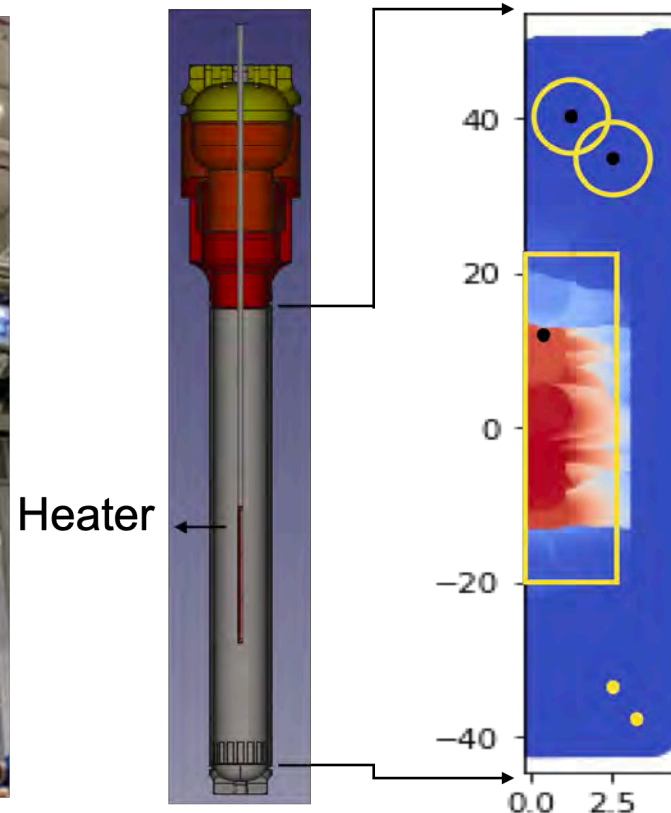
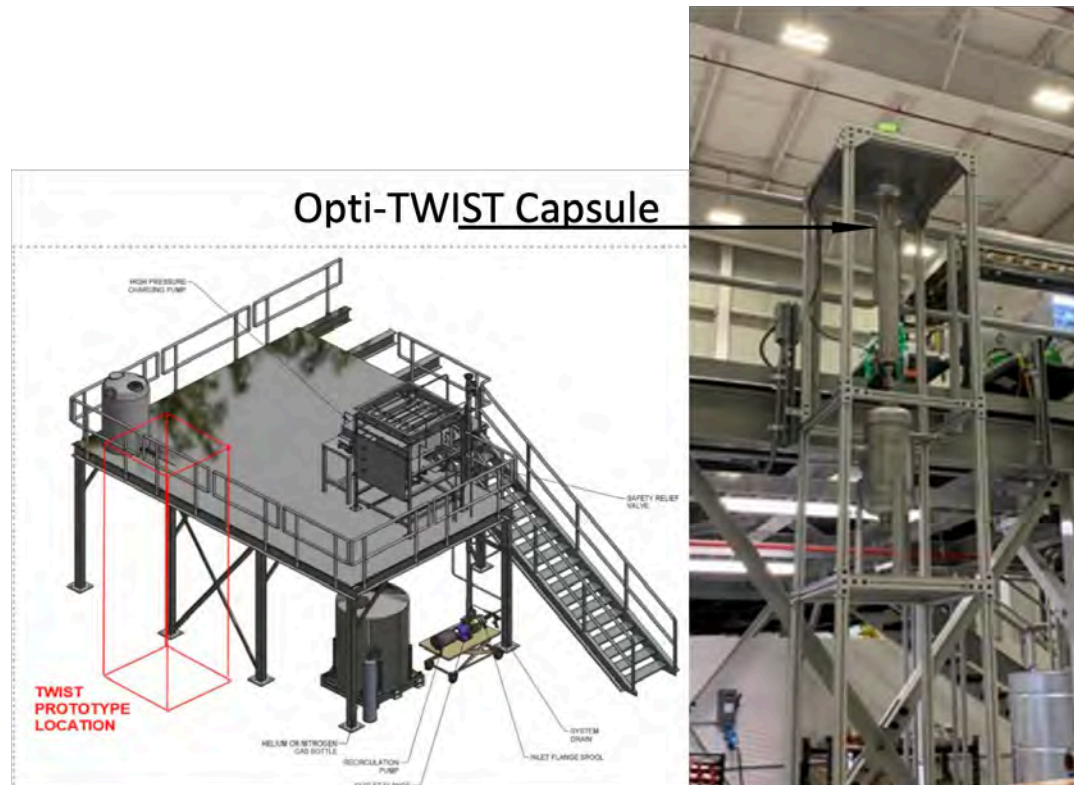




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GOAL: Reconstruct temperature profile with minimal sensors under :



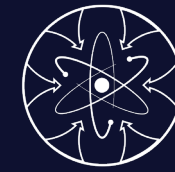
Distance Constraints

n = All possible sensor locations
 r = Selected sensors
 s_c = Constrained locations
 s = Maximum sensors in Constrained region

Region Constraints

User-specified Sensors

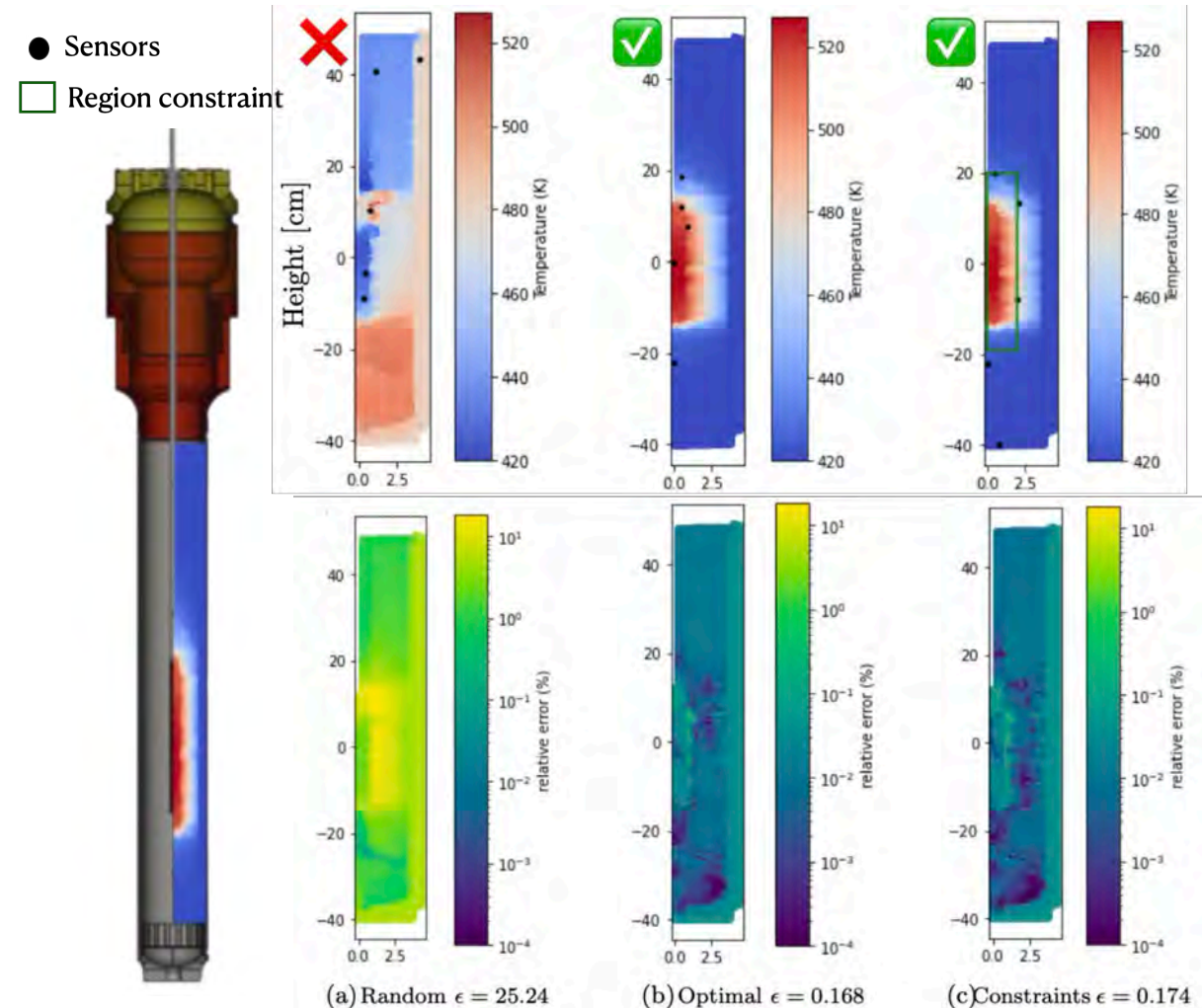
High Fidelity Thermal Reconstruction



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- Random sensor placement results in low accuracy and a distorted temperature profile across various power inputs.
- Sensors constrained outside the heater region provide low reconstruction errors across all power input samples.



High Fidelity Thermal Reconstruction

- Informed tradeoff between reconstruction accuracy and number of sensors (Fig 1).
- Lower uncertainty in field reconstruction despite noisy readings (Fig 2).

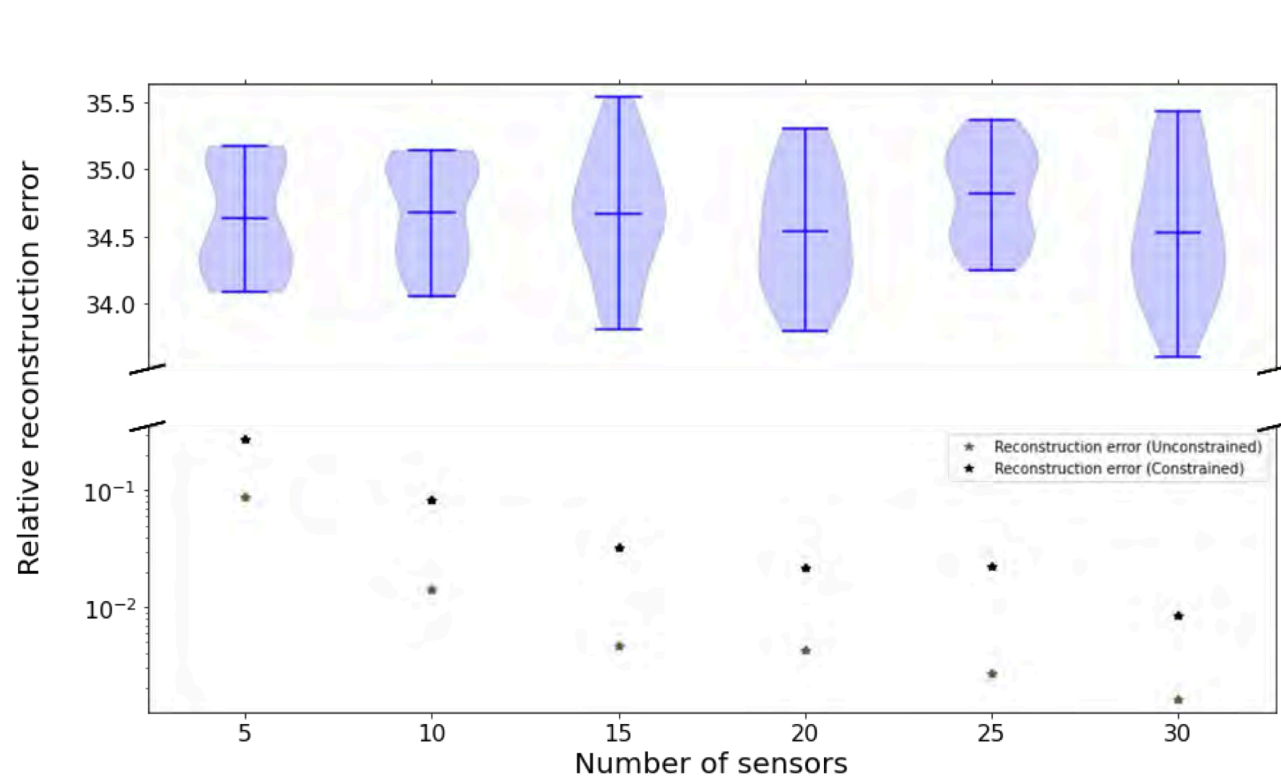


Fig 1: Informed tradeoff between reconstruction accuracy and number of sensors is possible for QR-optimized sensors.

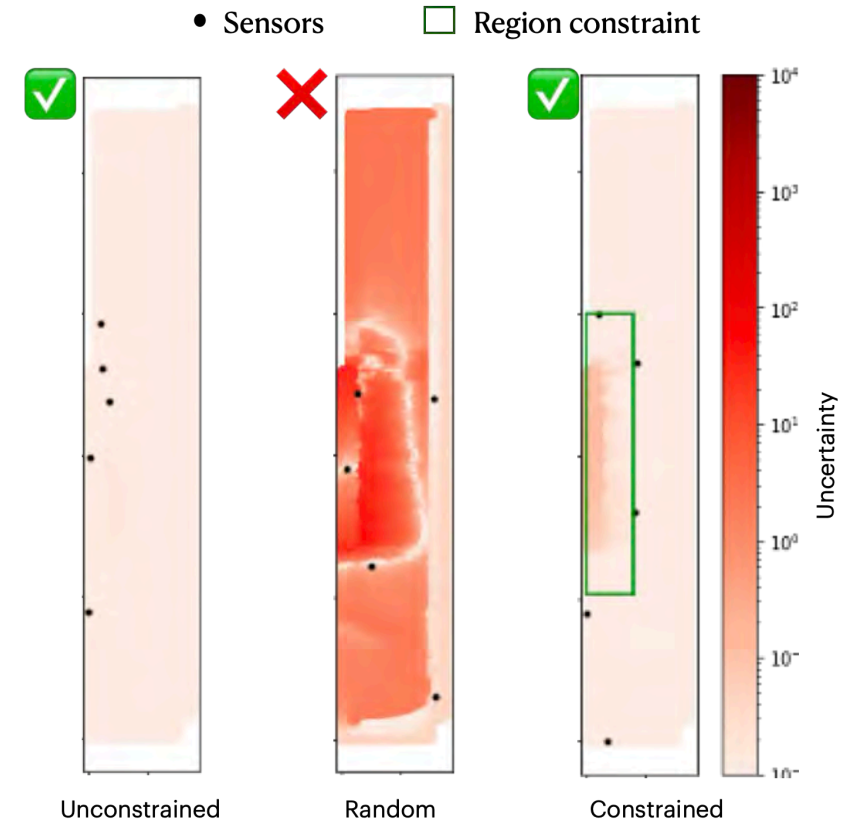
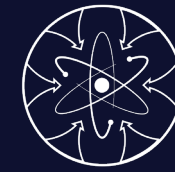


Fig 2: Noise-induced uncertainty in state reconstruction

Sensor optimization for Power Perturbations



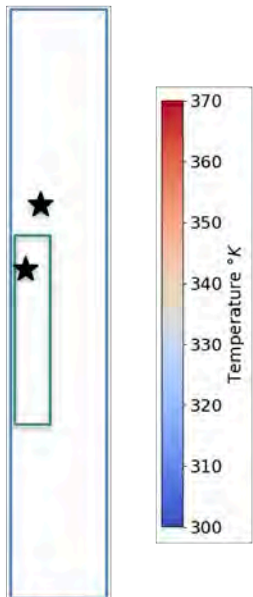
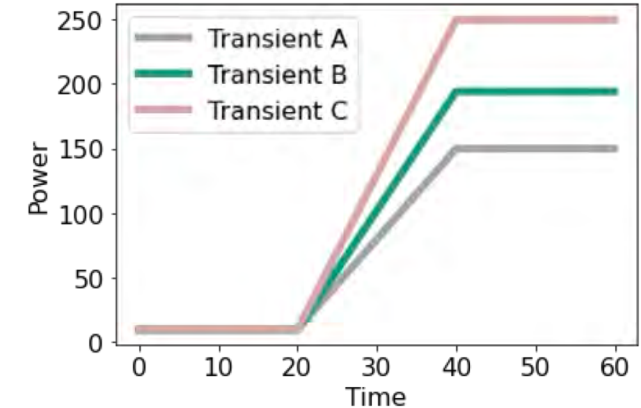
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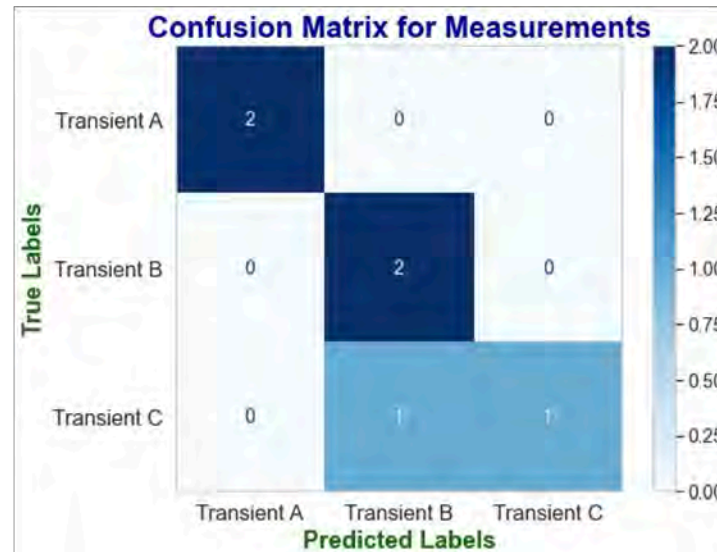
Previously: Focused on sensor placement for field reconstruction using steady-state temperature data.

Now: Consider time-dependent data from transients and power perturbations.

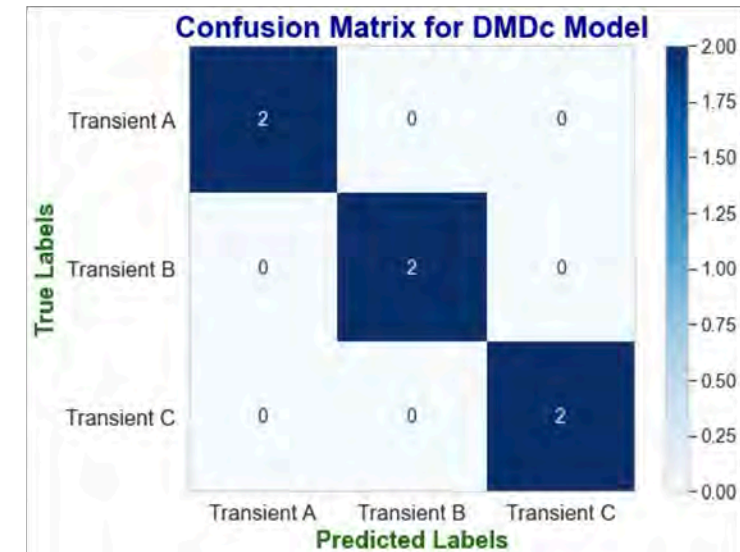
Goal: Place sensors that enable both field reconstruction and classifications of power inputs using dynamic mode decomposition with control.



Classifier trained on $\mathbf{y}_k$

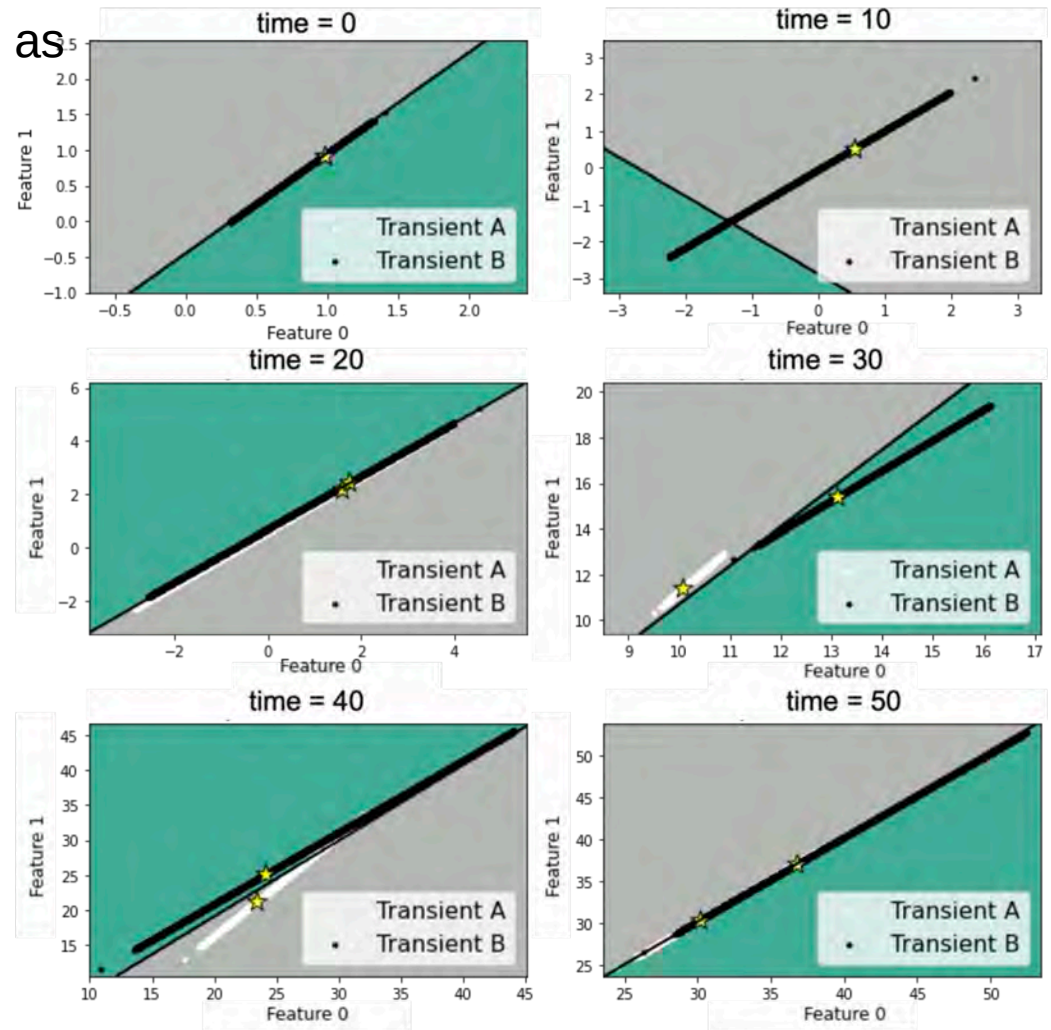
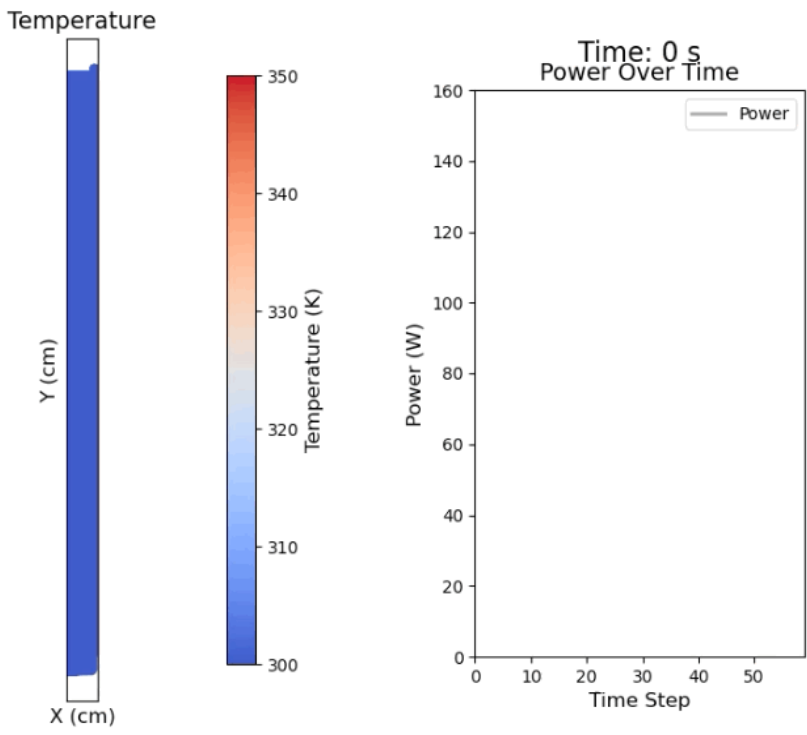


Classifier trained on $\hat{\mathbf{y}}_k - \Phi \Lambda^{k-1} \Phi^\dagger \hat{\mathbf{y}}_0$

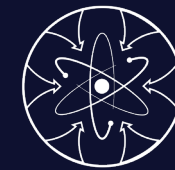


Classification of Power Inputs from Sensors

Once transient begins the two transients become highly separable as seen in the Figure.



Experimental Analysis of Power Perturbations



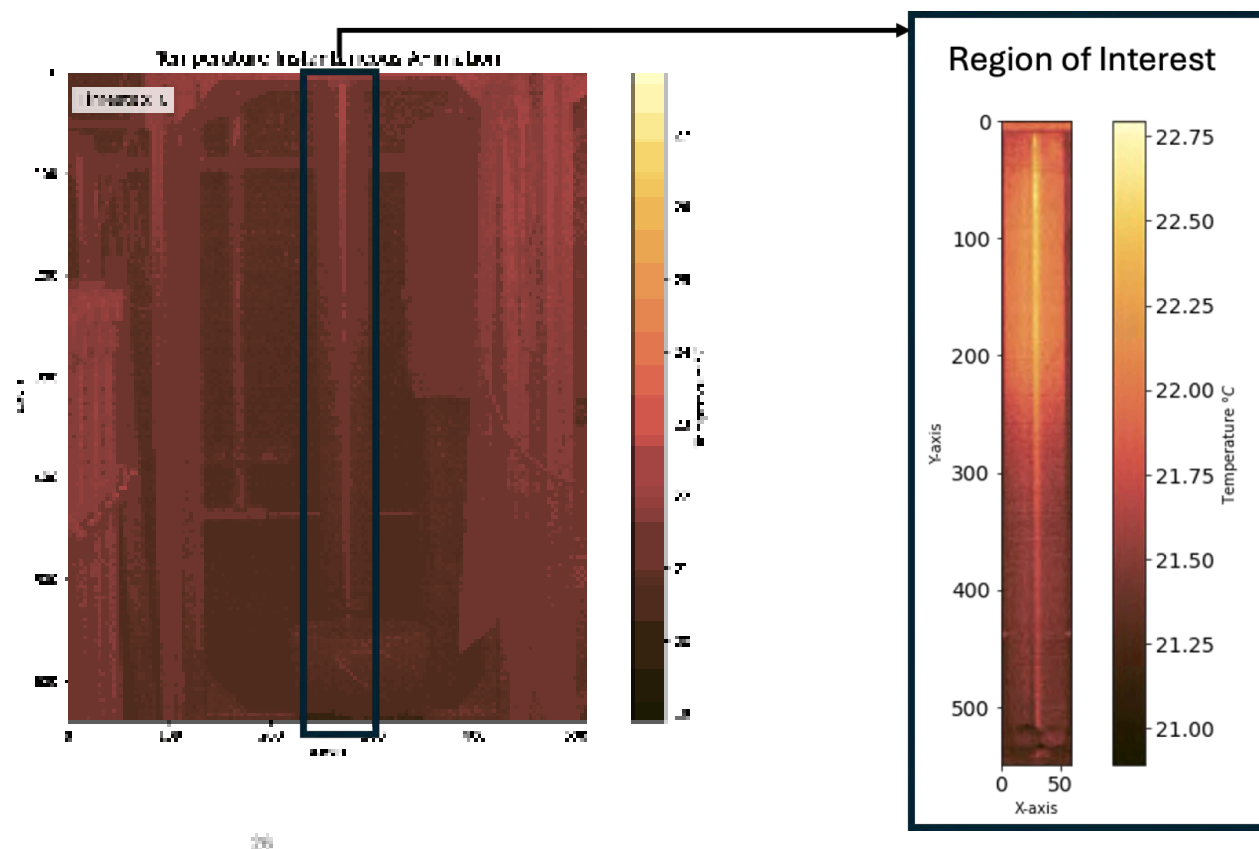
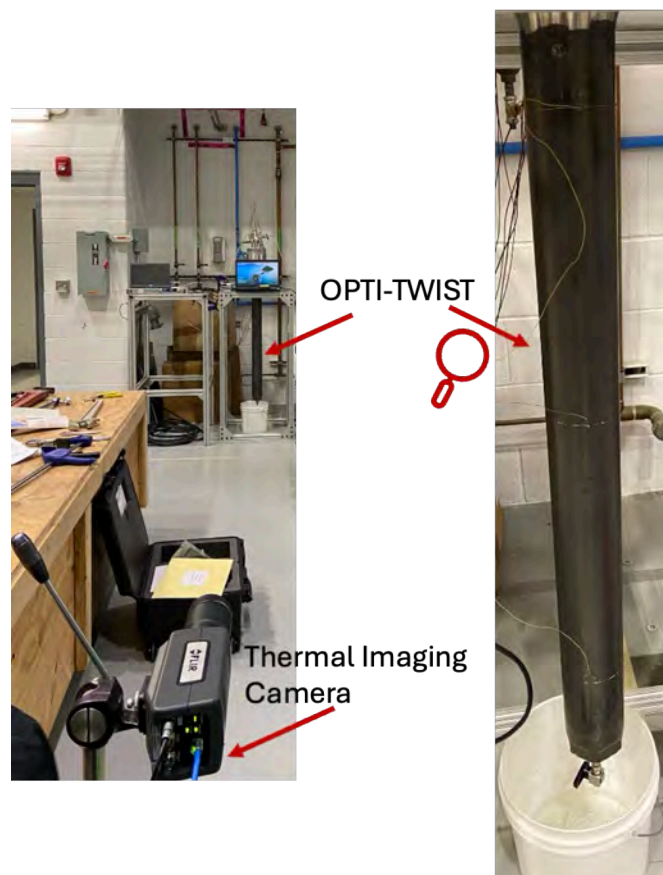
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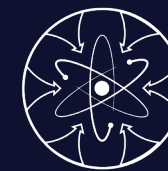
Real-time experimental validation of these methods is crucial for safety and licensing.

Experiments with thermal imaging of the OPTI-TWIST with heater power perturbations were performed at INL (Fig 1).

We confirmed that we can distinguish between different heater settings from thermal data alone (Fig 2).



Experimental Analysis of Power Perturbations



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- Random sampling of thermal images results in incorrect classification of the 1200W power profile (Fig 1).
- QR-determined sensor measurements with LDA classifier achieves near-perfect performance with only one misclassification (Fig 2).
- DMDC model delivers 100% classification accuracy across all power profiles as it captures the effect of control input (Fig 3).

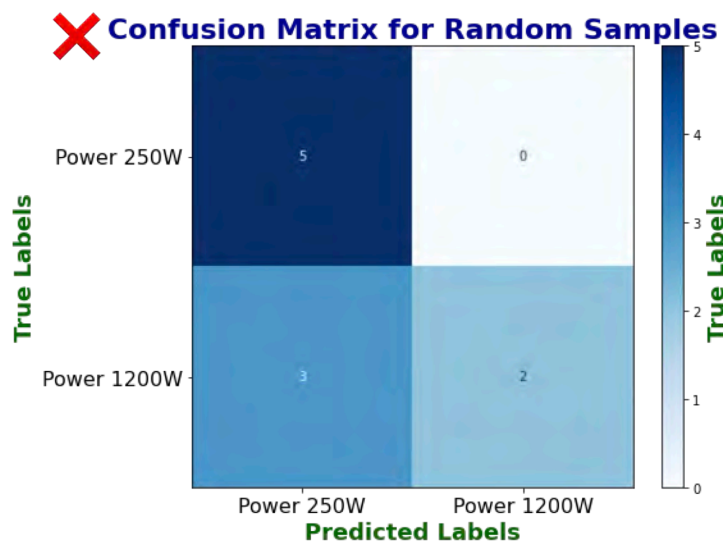
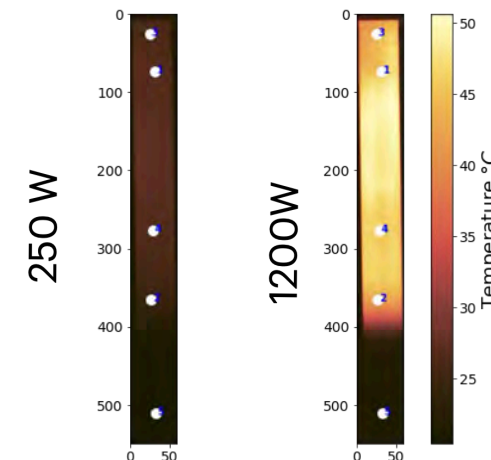


Fig 1

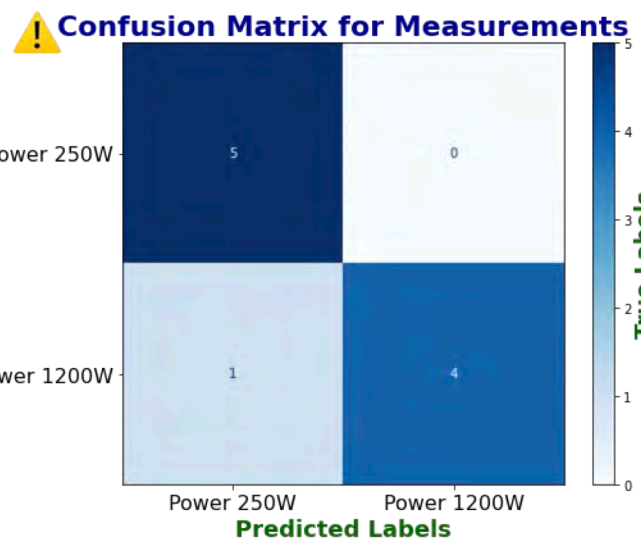


Fig 2

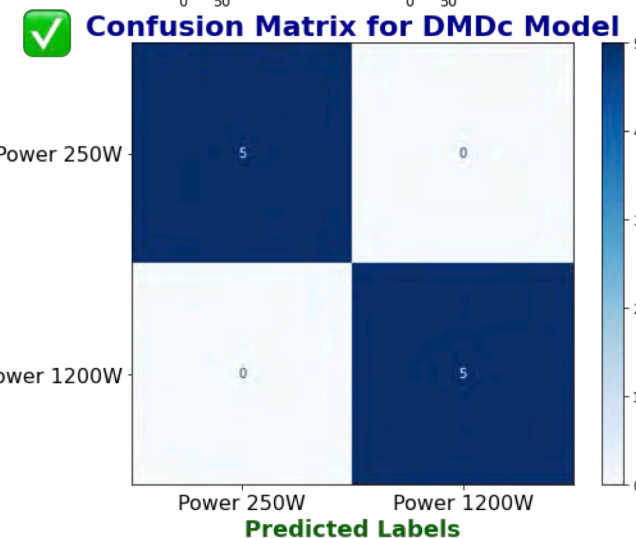


Fig 3

Case Study 2: TRISO Fuel Irradiation

- TRISO fuel temperature monitoring during irradiation is challenging due to extreme temperatures (1200-1300° C)
- Select optimal thermocouple locations from green holes (5-1 to 5-19) to reconstruct temperatures (Fig 2 - Solid Fuel).

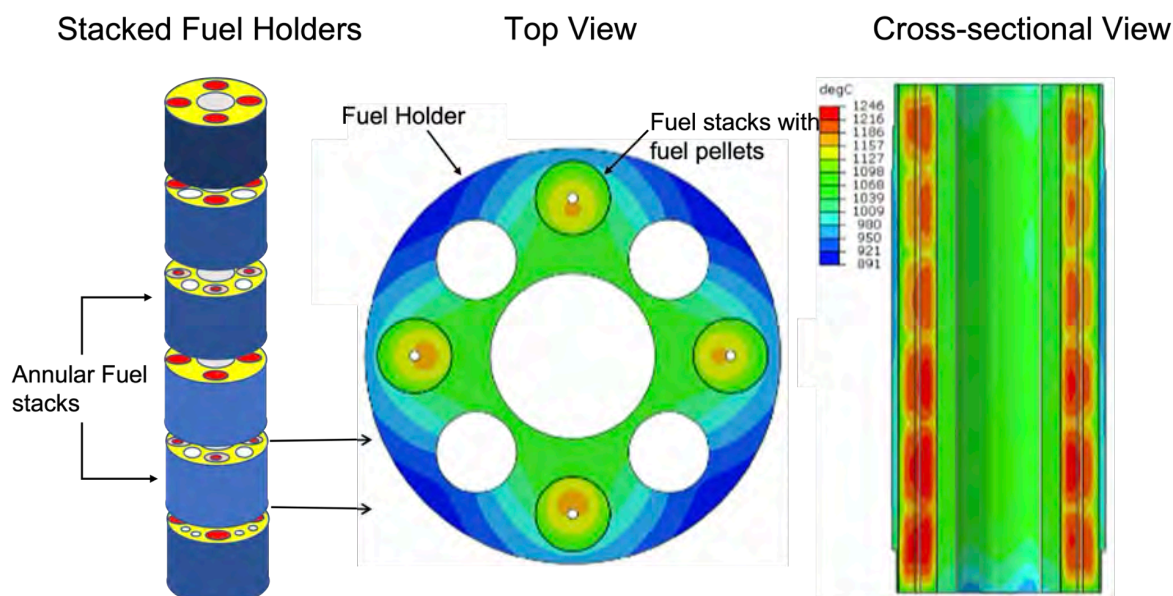
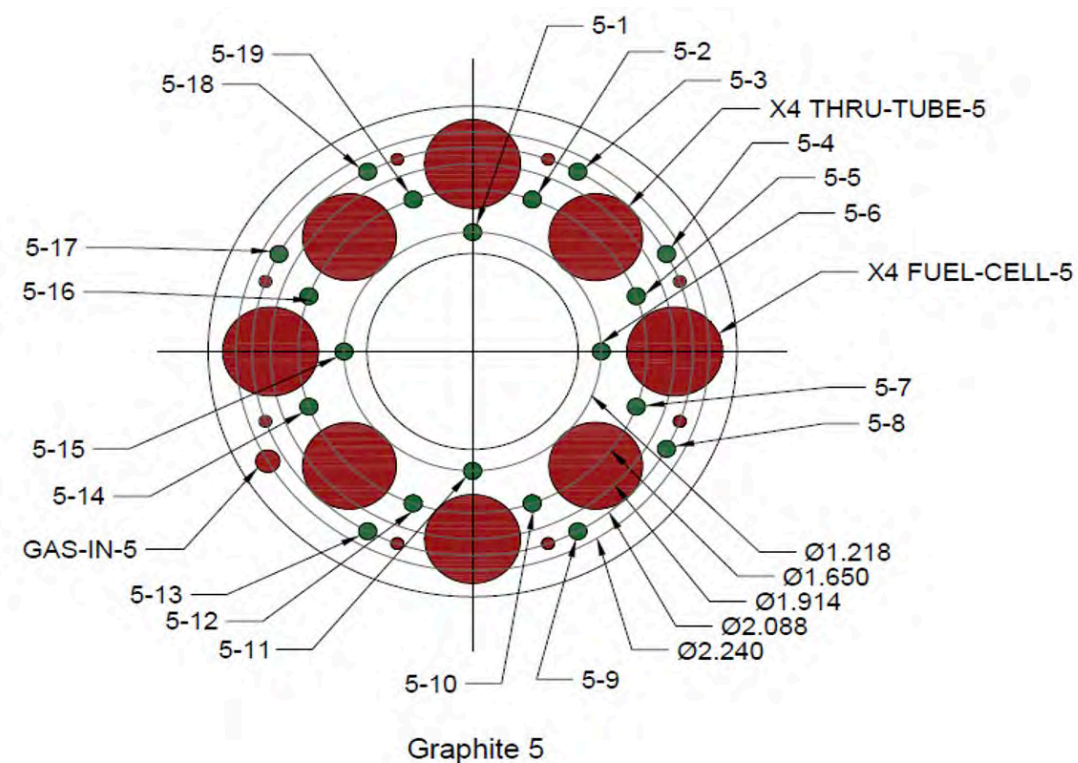
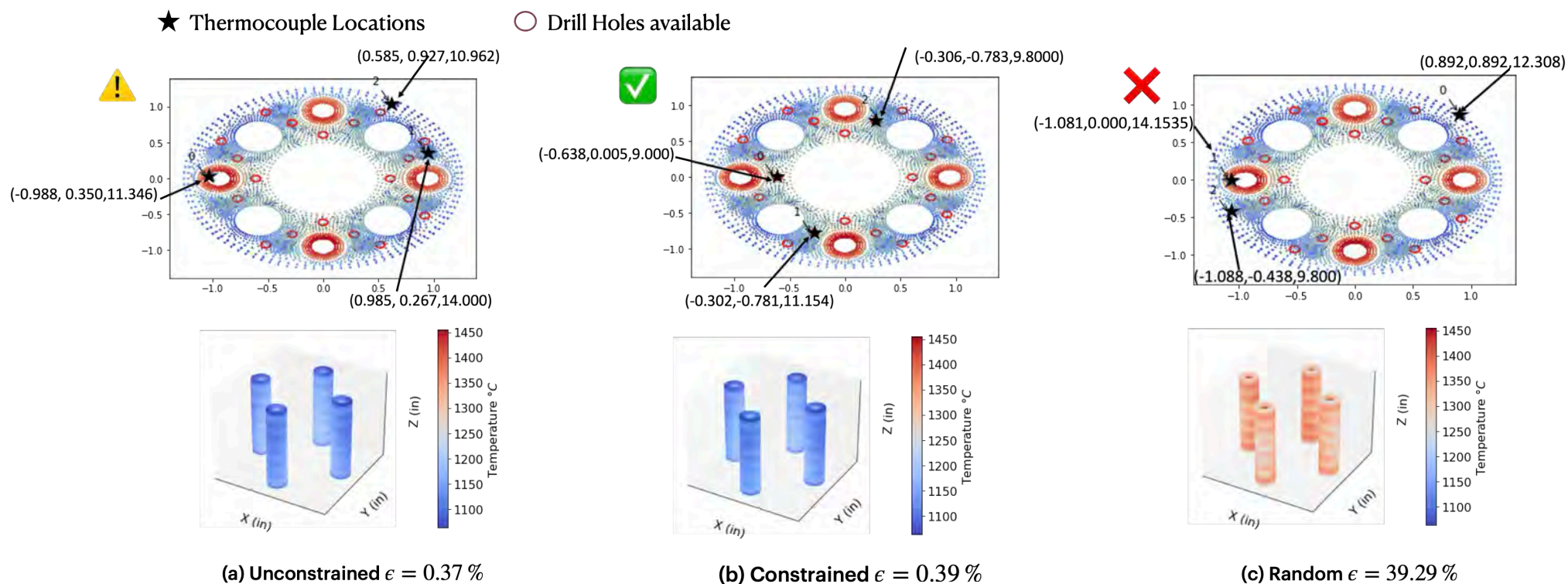


Fig 1: Stack of TRISO fuel showing solid and annular pellets for irradiation experiments. Annular fuel enables accurate temperature measurements through thermocouple penetration, while solid fuel does not permit TC access.



Case Study 2: TRISO Fuel Irradiation

- Unconstrained sensor locations (a) are infeasible as thermocouples would be placed directly in the fuel.
- Algorithm constrains thermocouples to feasible structural holes (red circles) (b) with drill depth determined by Z coordinate.



Case Study 3: Steam Generator Design

Temperature and heat flux are critical in steam generators, but phase change makes CFD modeling difficult. 1D phase change models with built-in phase change regions provide valuable insight into the thermal-hydraulic behavior (Fig 1).

POD modes from temperature data alone reveal underlying heat flux characteristics (Fig 2).

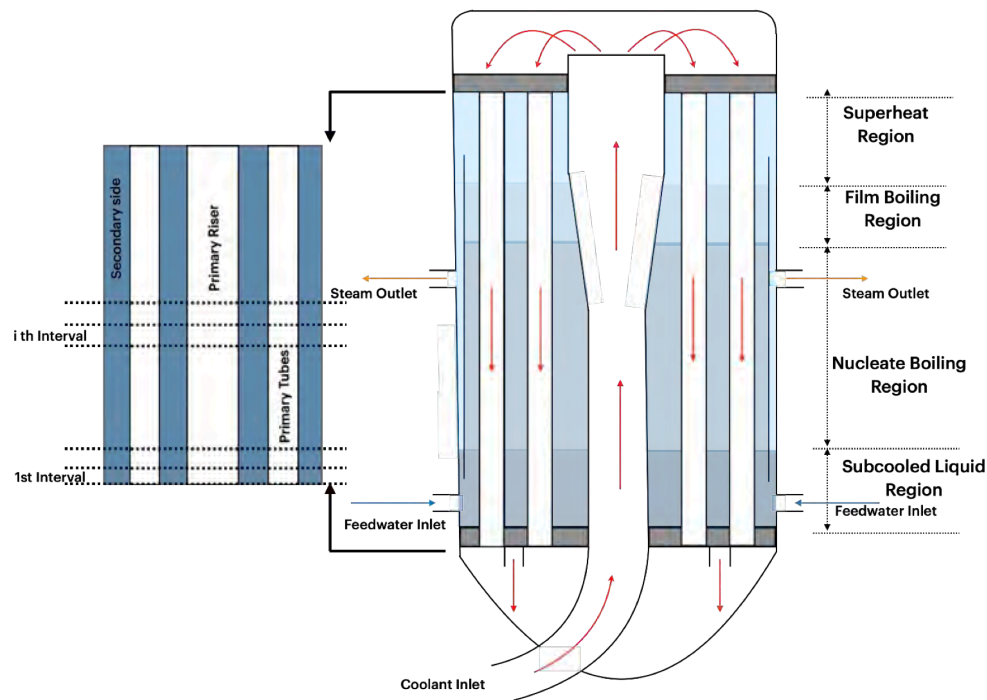


Fig 1: 1D Phase Change Steam Generator Model

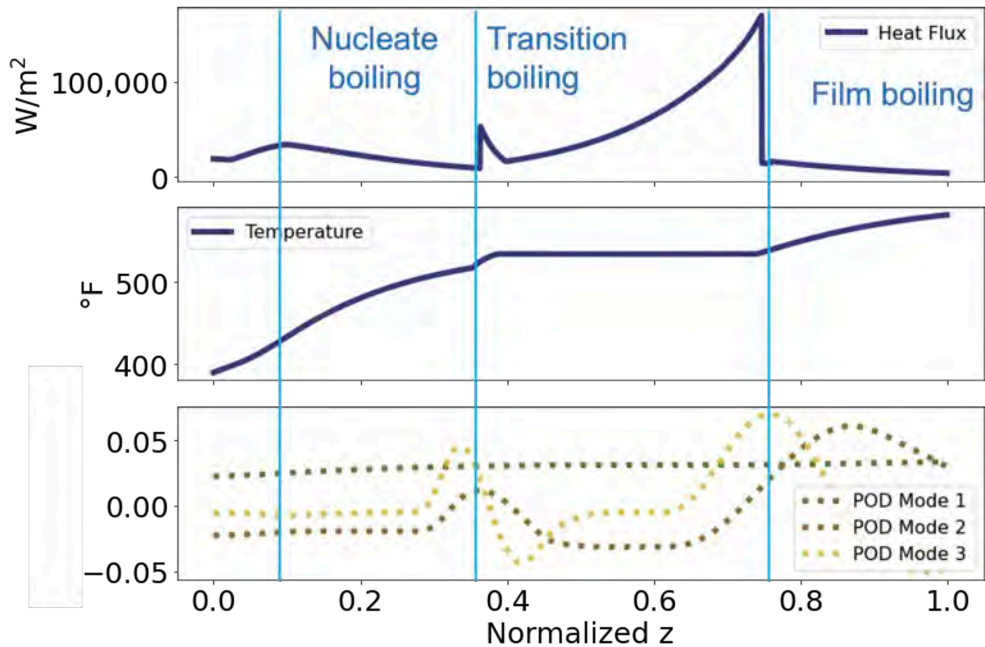
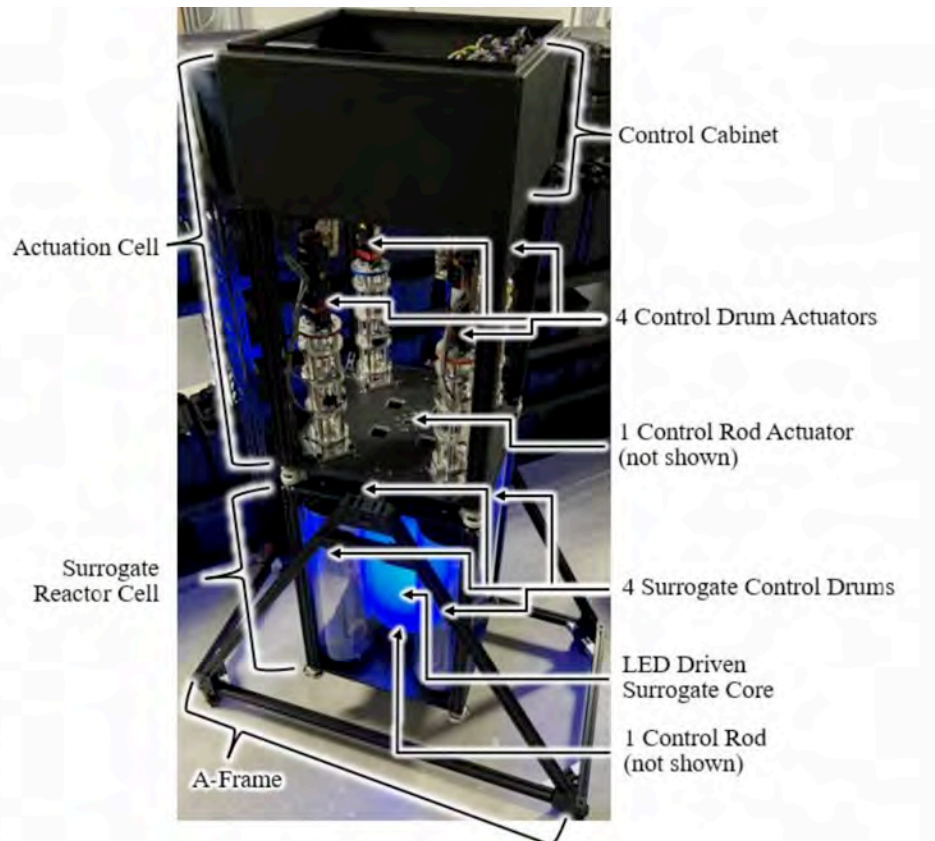
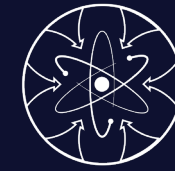


Fig 2: The 1st 3 POD modes capture 99% of energy content. 1st mode represents overall temperature profile and 2nd, 3rd modes capture heat flux variations along the steam generator height.

- Sensor optimization for field reconstruction of the Visual Benign Reactor as Analog for Nuclear Testing (ViBRANT) which represents primary reactor behaviors through accessible LED driven reactor core for actual microreactor deployment such as MARVEL.



Results and Accomplishments

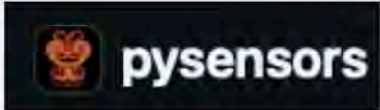


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- Implemented in Pysensors which provides constraint plotting capabilities to visualize feasible sensor placement regions and highlight changed sensors in red based on constraint boundaries.

```
circle = ps.utils._constraints.Circle(center_x = 20, center_y = 5, radius = 5,  
    loc = 'in', data = X_train)  
circle.draw_constraint()  
circle.plot_constraint_on_data(plot_type='image')  
circle.plot_grid(all_sensors=all_sensors)  
const_idx, rank = circle.get_constraint_indices(all_sensors =  
    all_sensors_unconst, info= X_train)  
s = 4  
optimizer = ps.optimizers.GQR()  
optimizer_kwargs={'idx_constrained':const_idx,  
    'n_sensors': r,  
    'n_const_sensors': s,  
    'all_sensors':all_sensors,  
    'constraint_option':"exact_n"}
```



- Pysensors integrates seamlessly with RAVEN, INL's digital twin platform, enabling advanced sparse sensing capabilities within comprehensive simulation frameworks.

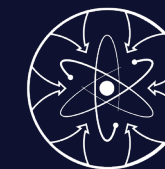
```
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  <Goal subType="reconstruction">  
    <features>X (m),Y (m),Temperature (K)</features>  
    <target>Temperature (K)</target>  
    <basis>SVD</basis>  
    <nModes>4</nModes>  
    <nSensors>4</nSensors>  
    <optimizer>QR</optimizer>  
  </Goal>  
</PostProcessor>  
</Models>
```



[1] Rabiti C, Alfonsi A, Mandelli D, Cogliati JJ, Wang C, Talbot PW, Malijovec DP, Kinoshita RA, Abdo MG, Sen S, Chen J. RAVEN user manual. Idaho National Laboratory (INL), Idaho Falls, ID (United States); 2021 May 19.



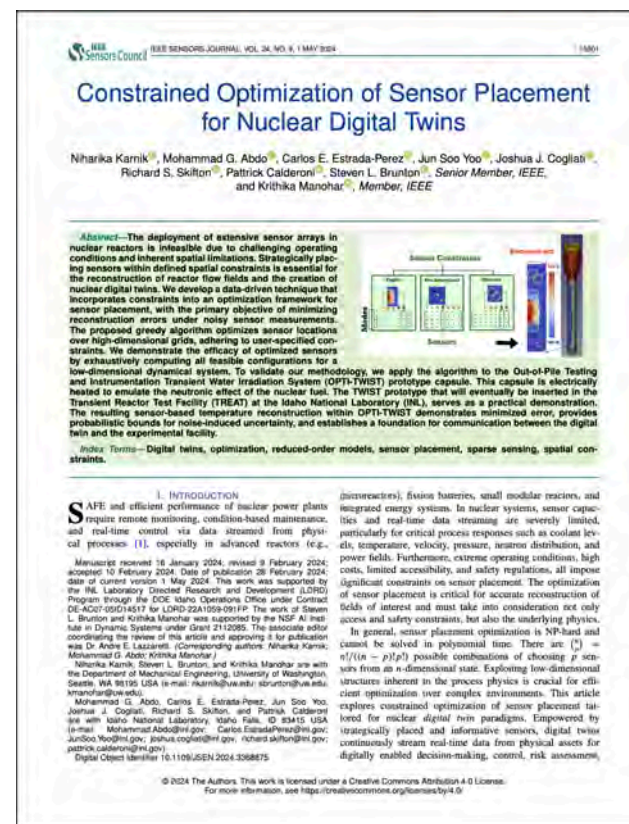
Results and Accomplishments



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- Full Field Reconstruction from Optimally Placed X Sparse Sensors **Outperforms 4X** random sensors by **Several Orders of magnitudes** of accuracy.
- Future work includes extending the sensor placement to **anomaly** and **off-normal conditions detection**.
- Intellectual property/copy rights: RAVEN Sparse Sensing Postprocessor
<https://github.com/idaholab/raven/blob/devel/ravenframework/Models/PostProcessors/SparseSensing.py>

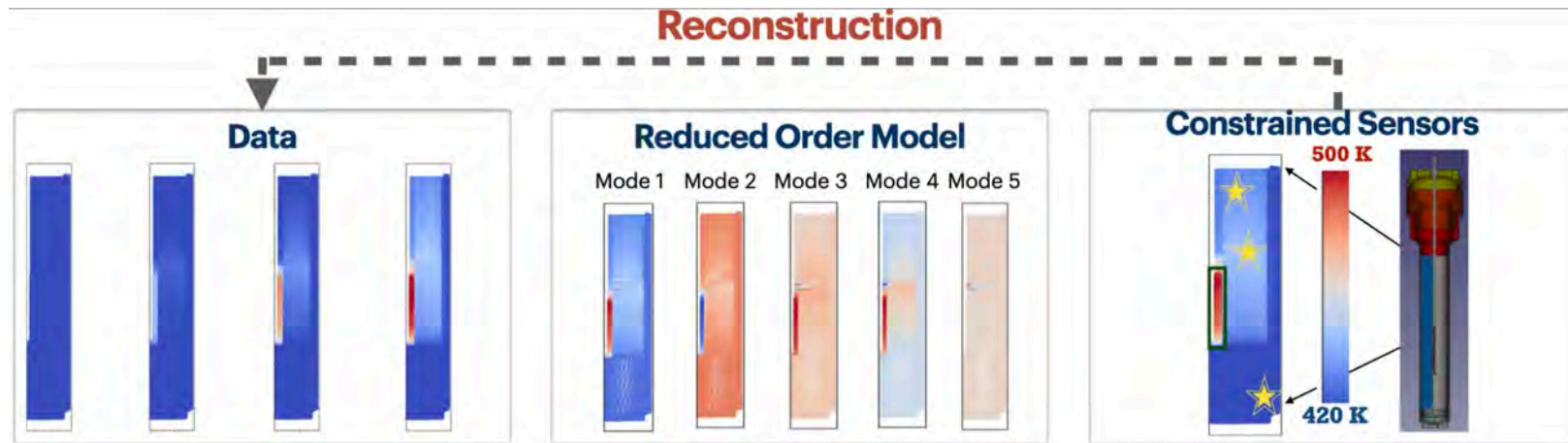


U.S. DEPARTMENT
of **ENERGY**

Office of
Nuclear Energy

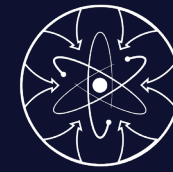
Concluding Remarks

- Sensor based **reconstruction** enables real-time monitoring of the temperature field.
- Compared to randomly placing sensors, **constrained locations** show higher reconstruction accuracy.
- Established error covariance bounds can 'flag' **recalibration** of the digital twin model.
- **Uncertainty estimation** from noisy sensor measurements enables digital twinning of nuclear assets.
- **Classification** and reconstruction of original power inputs from sensors data highlight potential for detecting and analyzing anomalies in input patterns, paving the way for predictive maintenance and fault diagnosis.



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C-230 Plant Optimization

- Karnik, N., Abdo, M. G., Estrada-Perez, C. E., Yoo, J. S., Cogliati, J. J., Skifton, R. S., ... & Manohar, K. (2024). "Constrained optimization of sensor placement for nuclear digital twins." IEEE Sensors Journal.
- Karnik N, Wang C, Bhowmik PK, Cogliati JJ, Balderrama Prieto SA, Xing C, Klishin AA, Skifton R, Moussaoui M, Folsom CP, Palmer JJ., Sabharwall P, Manohar K, Abdo MG, Leveraging Optimal Sparse Sensor Placement to Aggregate a Network of Digital Twins for Nuclear Subsystems. Energies (19961073). 2024 Jul 1;17(13).
- Karnik N, Bhangale Y, Abdo MG, Klishin AA, Cogliati JJ, Brunton BW, Kutz JN, Brunton SL, Manohar K. PySensors 2.0: A Python Package for Sparse Sensor Placement. arXiv preprint arXiv:2509.08017. 2025 Sep 9.
- Karnik, N., M. G. Abdo, and K. Manohar. "Optimal Sparse Sensor Placement with Adaptive Constraints for Nuclear Digital Twins." 75th Annual Meeting of the APS Division of Fluid Dynamics (APS DFD 2022) November 20-22, 2022, Indianapolis, IN.
- DICE 2024: presentation about applications of sparse sensing in nuclear digital twins.
- Karnik, N., Abdo, M. G., Manohar K. "Data-Driven Sensor Placement for Nuclear Reactor Transient Analyses in Digital Twins". Bulletin of the American Physical Society (APS DFD 2023)
- Karnik N, Manohar K, Abdo M. Sensor Optimization of Nuclear Reactor Subsystems within a Digital Twin Network. In APS Division of Fluid Dynamics Meeting Abstracts 2024 Nov (pp. J11-003).
- AI Institute in Dynamic Systems CTF workshop (Sponsored by NSF)
- PHSOR 2024, Scientific ML workshop: "Sparse sensing and Sparse Learning for Nuclear Digital Twins."
- Karnik N. Data-Driven Modeling and Sparse Sensing for Nuclear Energy Systems (Doctoral dissertation, University of Washington).



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Backup Slides



Illustration of QR with Column Pivoting

QR factorization: Orthonormal Q, upper-triangular R, permutation $\mathbb{S}$

- $|\det \mathbb{S} \Phi_r| = \text{product of (magnitudes of) diagonal entries of R}$
- Pivot indices correspond to optimal sensor locations
- We enforce constraints by selecting the next pivot from the admissible locations.

Selecting sensors/pivots in the **admissible** locations

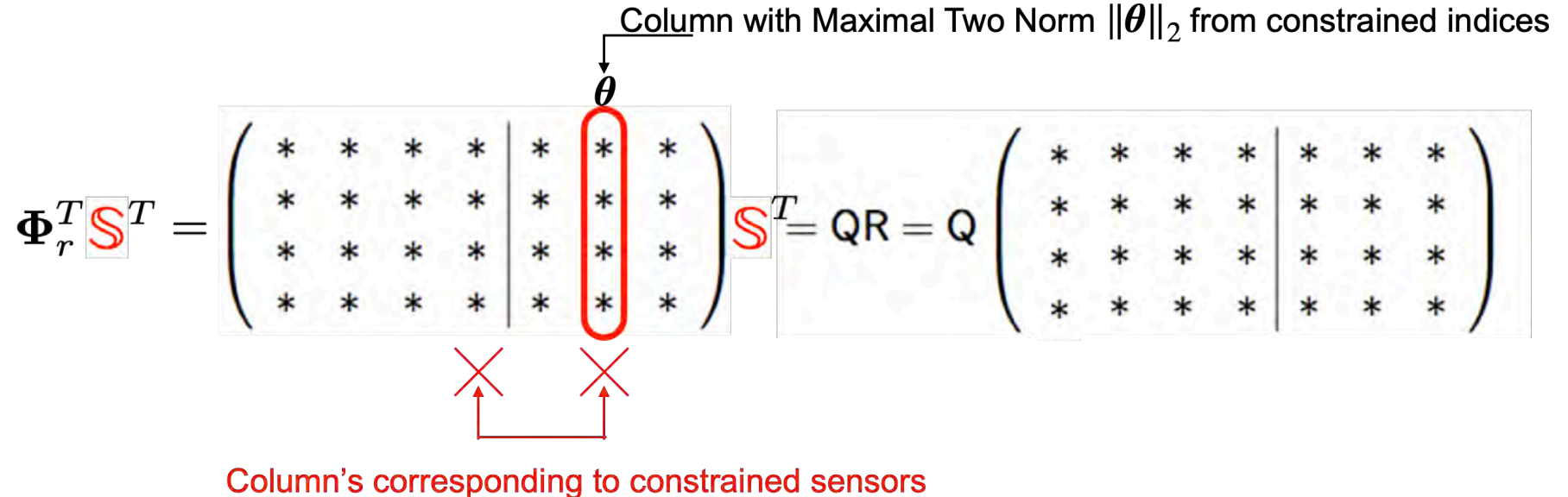


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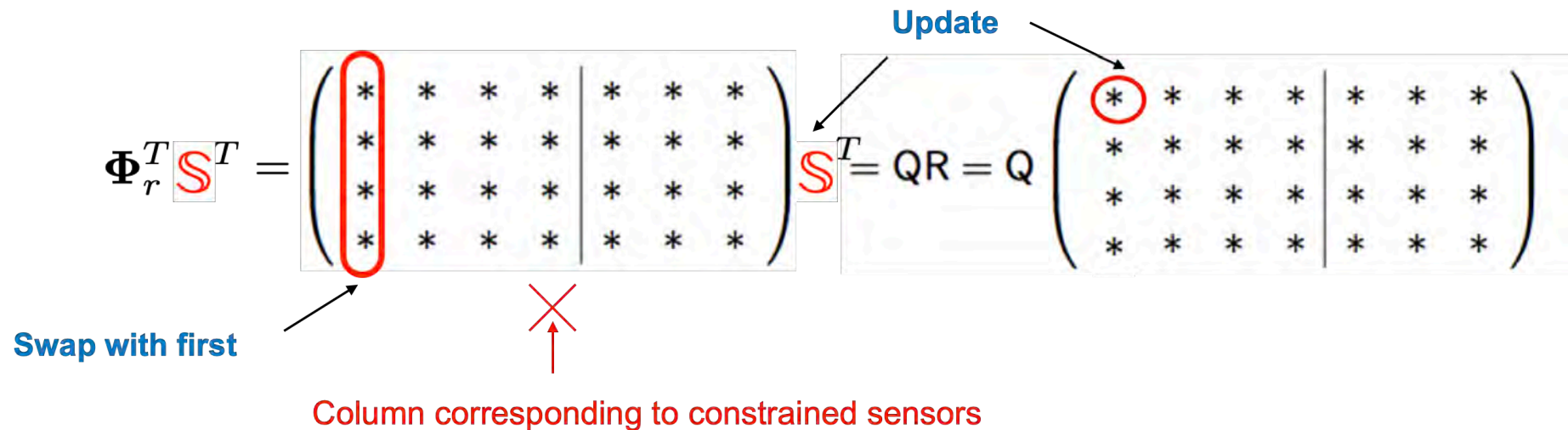


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Selecting sensors/pivots in the unconstrained locations

Column with Maximal Two Norm $\|\theta\|_2$ from unconstrained indices

$$\Phi_r^T \mathbb{S}^T = \left(\begin{array}{cccc|cccc} * & * & * & * & * & * & * & * \\ * & * & * & * & * & * & * & * \\ * & * & * & * & * & * & * & * \\ * & * & * & * & * & * & * & * \end{array} \right) \mathbb{S}^T = QR = Q \left(\begin{array}{cccc|cccc} * & * & * & * & * & * & * & * \\ * & * & * & * & * & * & * & * \\ * & * & * & * & * & * & * & * \\ * & * & * & * & * & * & * & * \end{array} \right)$$

θ

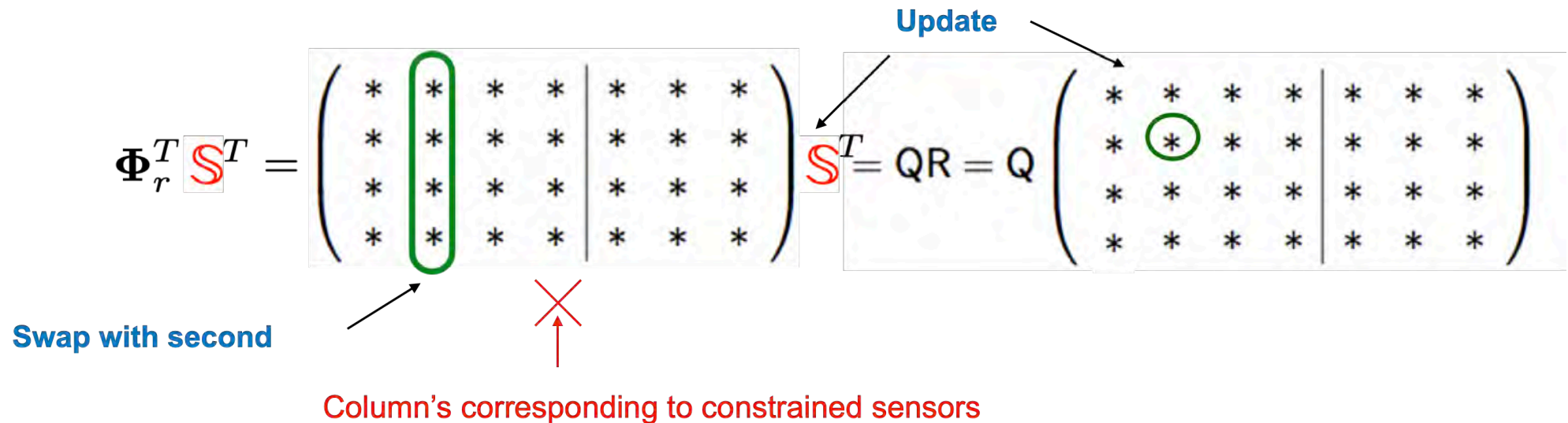
Column's corresponding to constrained sensors

Illustration of **QR** with Column Pivoting

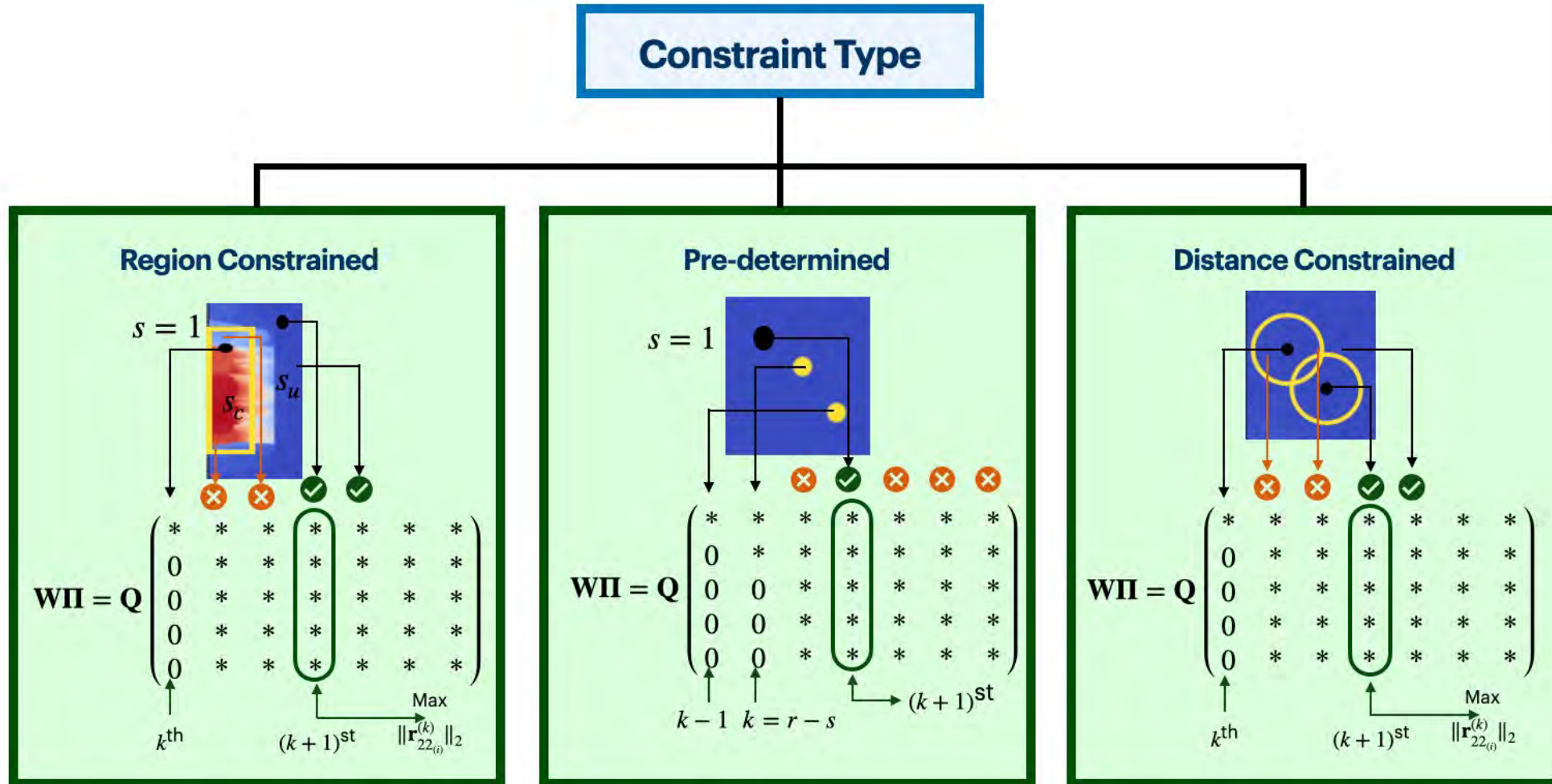
QR factorization: Orthonormal Q , upper-triangular R , permutation $\mathbb{S}$

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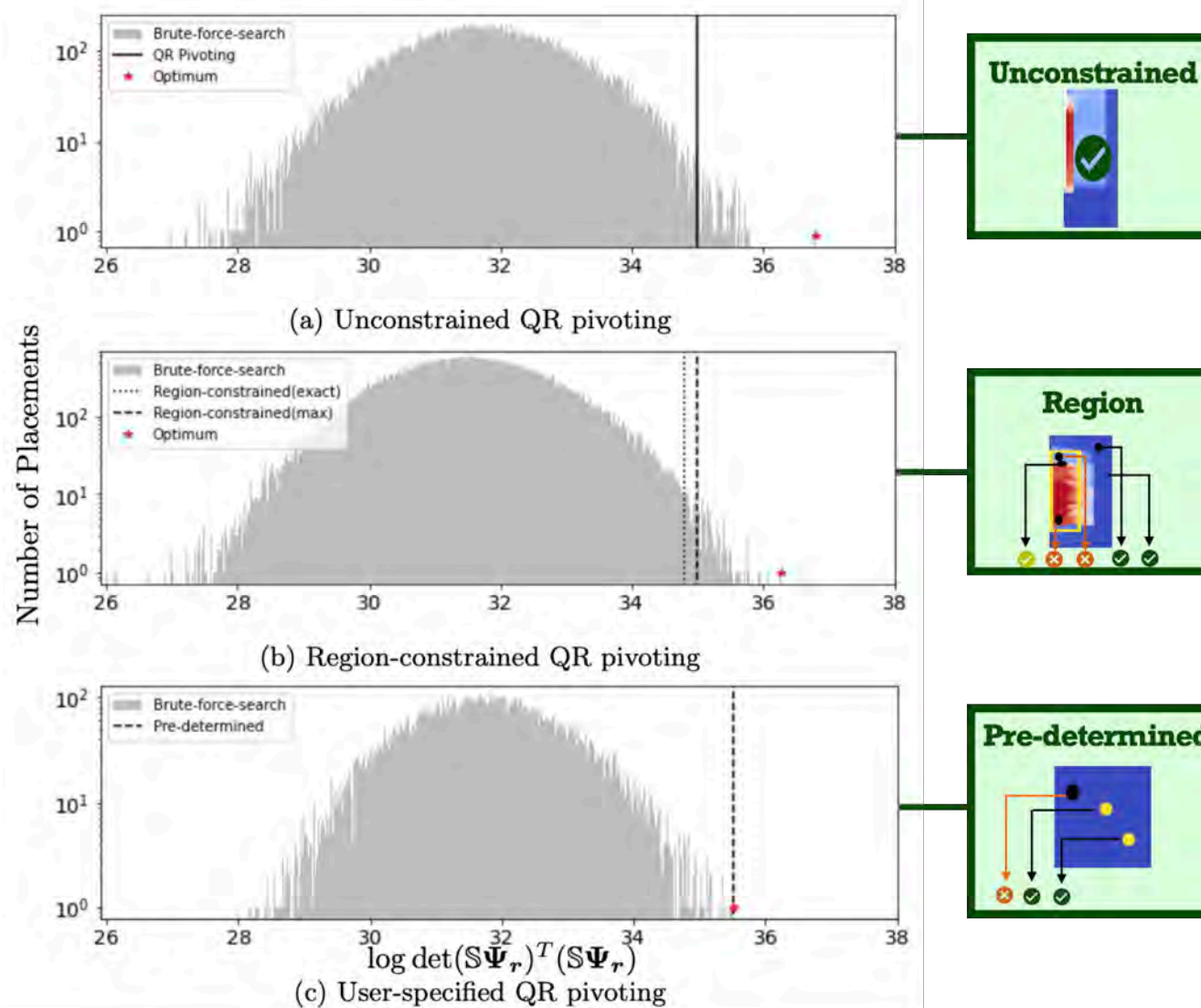
Selecting sensors/pivots in the **unconstrained** locations



Efficient greedy constrained optimization scheme: QR factorization



Validation through enumerating all possible placements



Visualization

1. Physical Space

(ASI, P&ID, BOM, Actuators)

2. Digital/Virtual Space

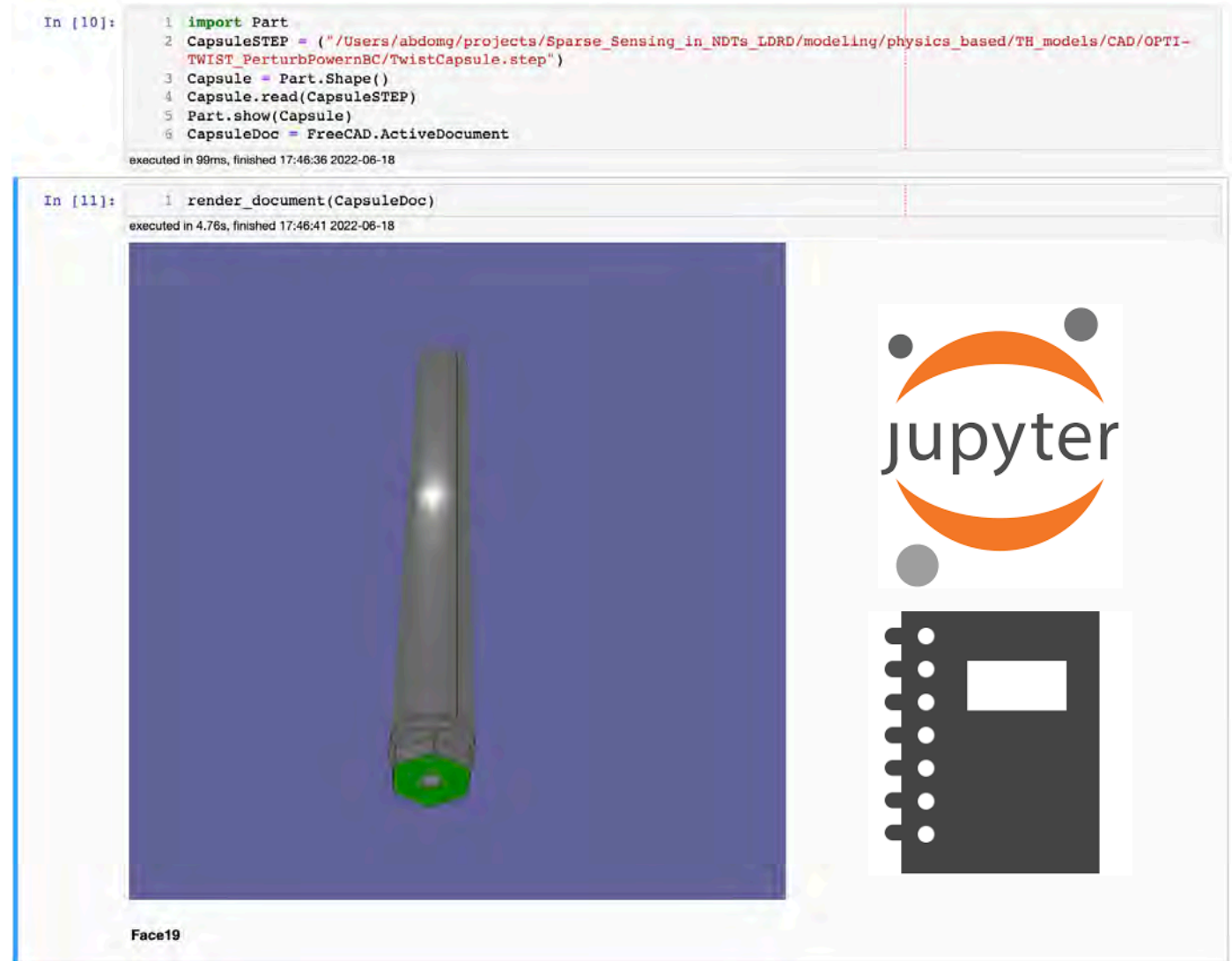
(CAD/GUIs/Analytics)

3. Data Space

(Storage, Connectivity, IIoT)

4. Services Space

(Prediction/Monitoring/Control)



Data warehouse

1. Physical Space

(ASI, P&ID, BOM, Actuators)

2. Digital/Virtual Space

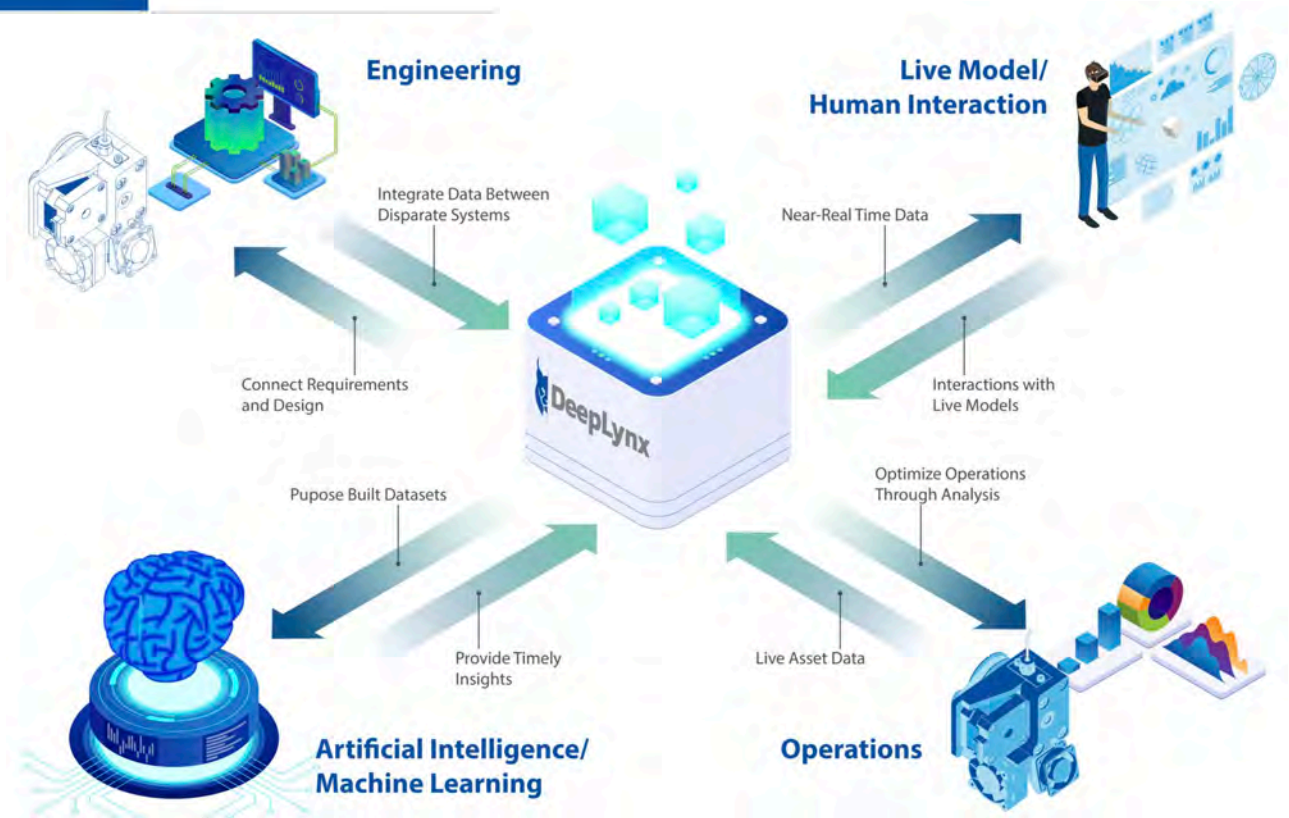
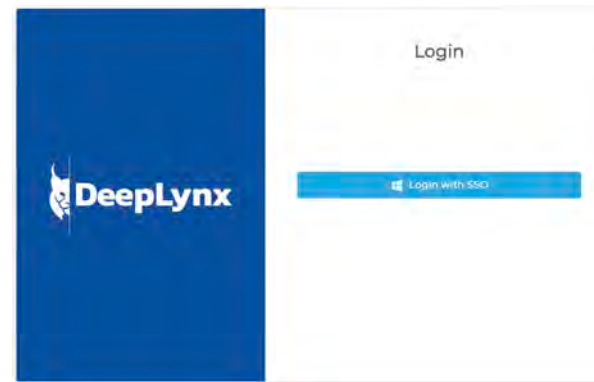
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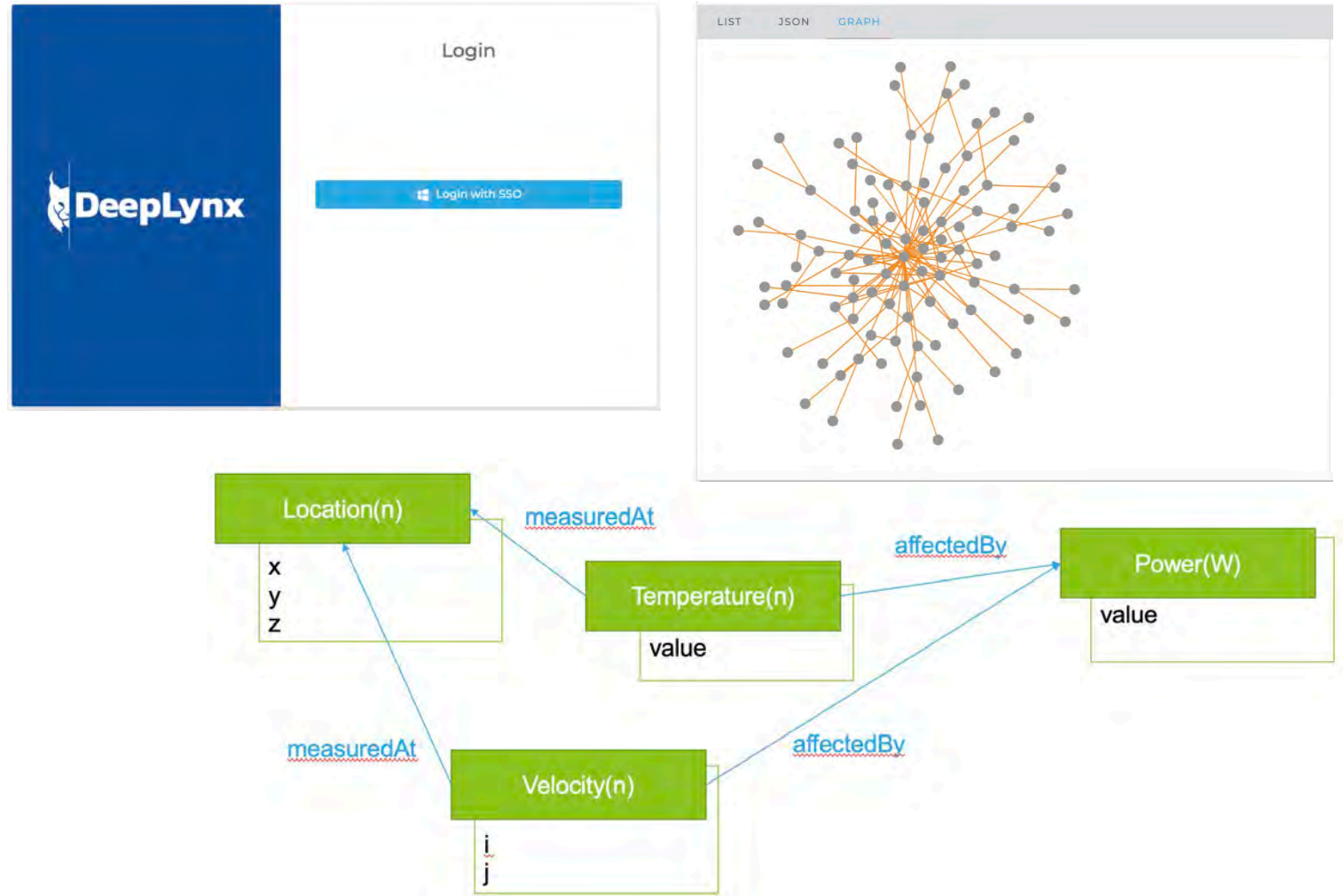
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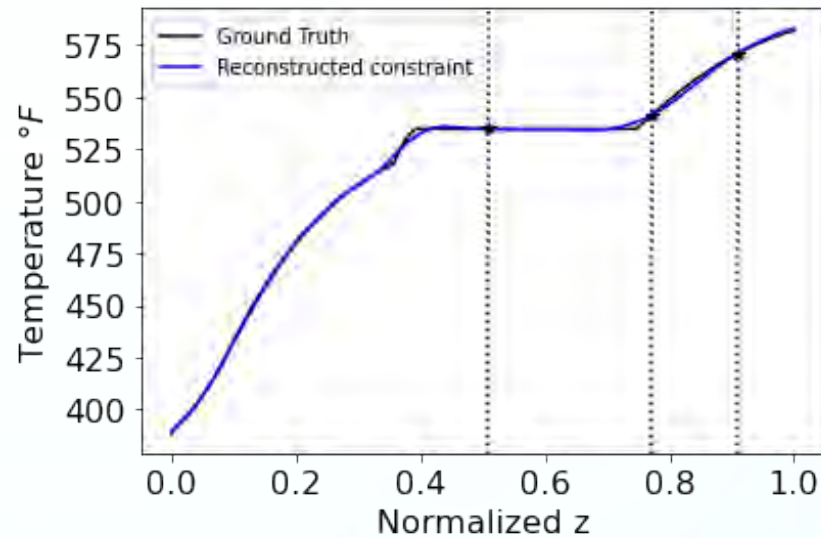
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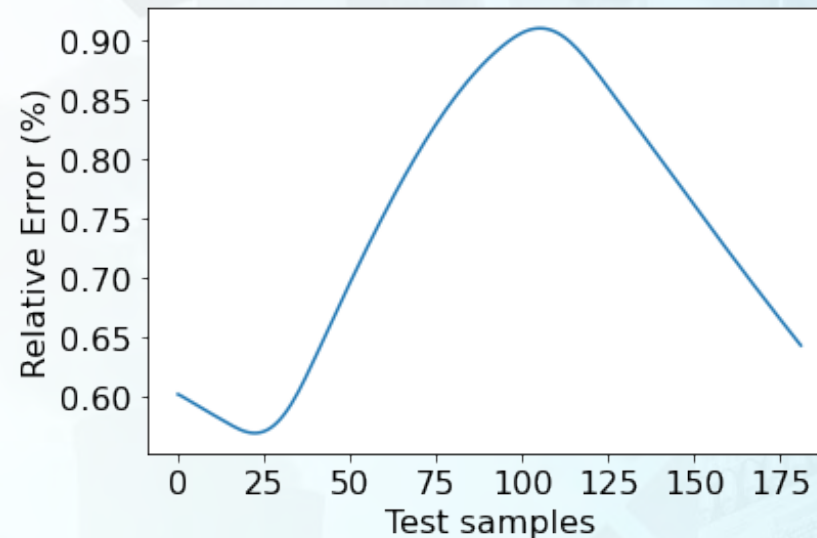
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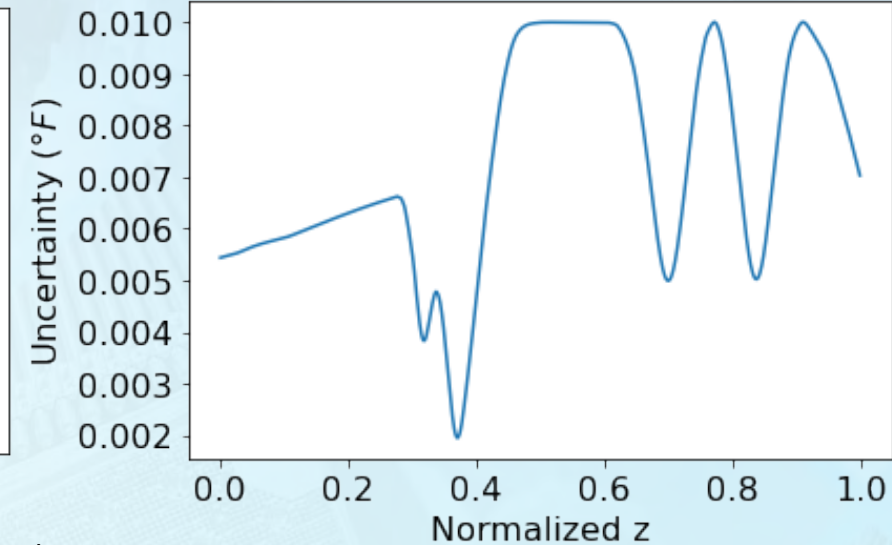




a) Constrained sensor reconstruction $\epsilon = 0.9\%$



(b) Max reconstruction error over all test samples is 0.9%



(c) High uncertainty in temperature transition zones

Secondary side temperature profile reconstructed from 3 constrained sensors results in a maximum reconstruction error of 0.9 % over all test samples (a,b) and the maximum uncertainty in reconstruction for noisy sensor measurements is 0.01 ° F (c).

