Improving Predictions Under Uncertainty of Material Plasma Device Operations

Workshop on AI for Accelerating Fusion and Plasma Science, IAEA, Vienna

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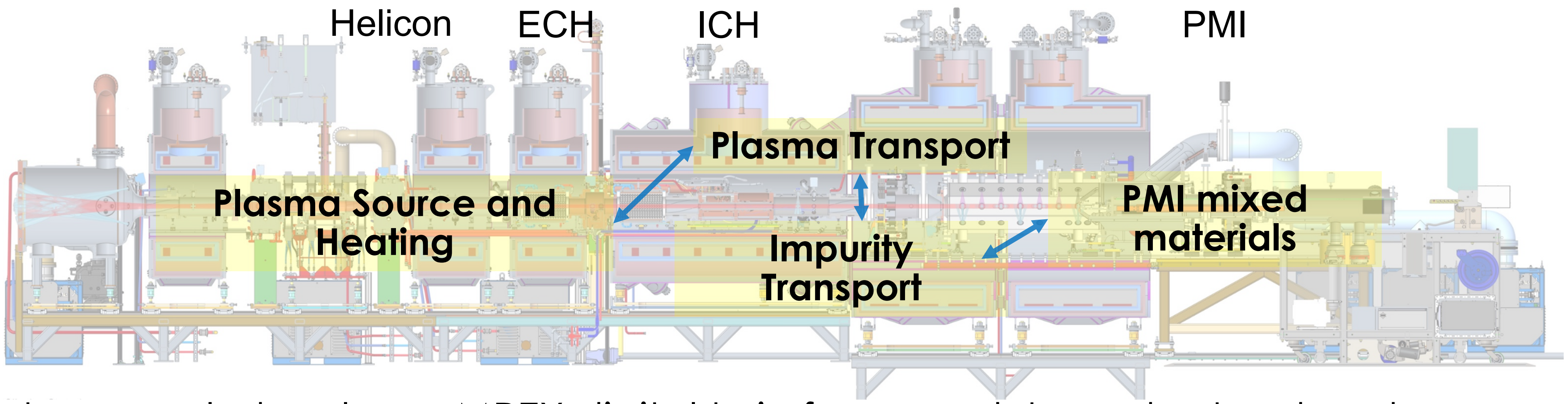
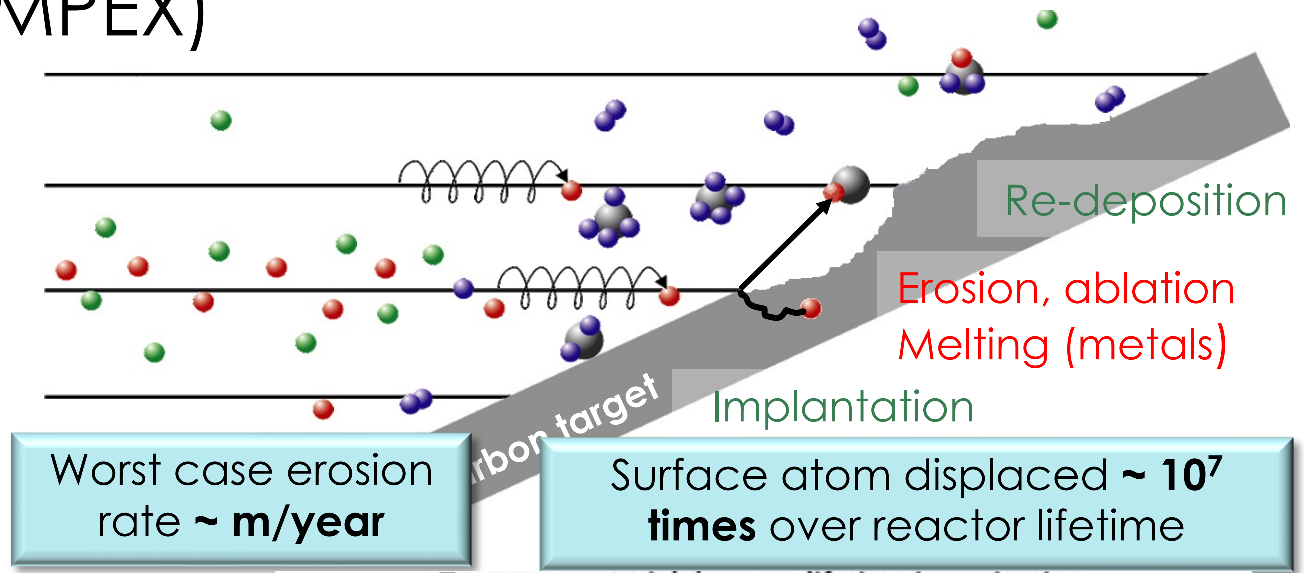
Develop a MPEX digital twin framework to accelerate MPEX commissioning of reactor-relevant fluxes and fluences



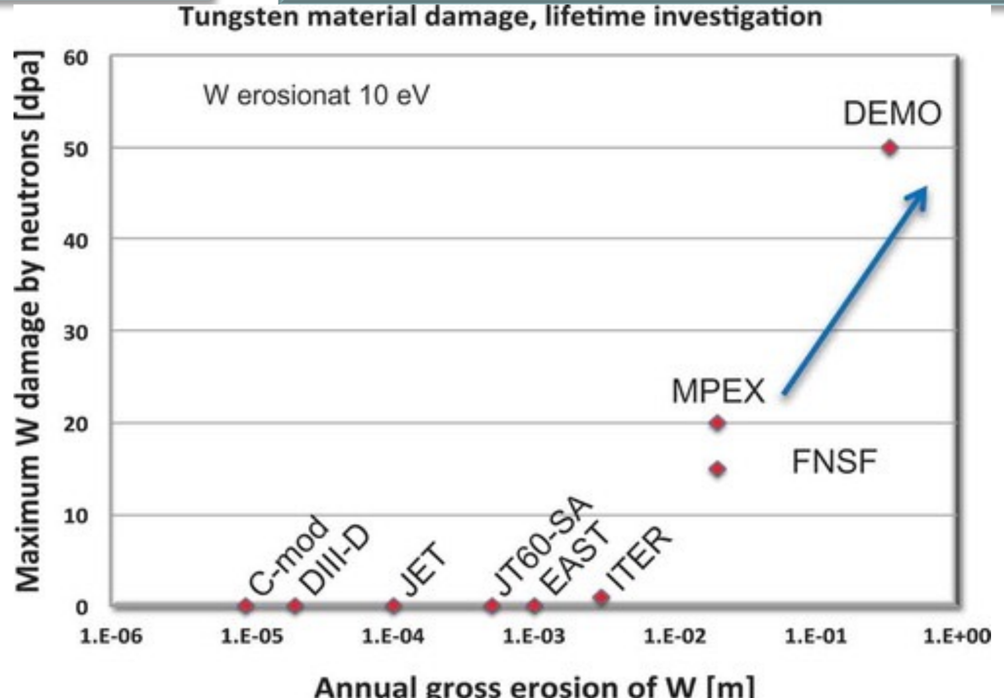
- Near term goal: develop a MPEX digital twin framework to understand and recommend solutions to maximize deuterium plasma fluxes and minimize impurity fluxes at PMI target
- Long term goal: apply MPEX digital twin to accelerate MPEX commissioning of reactor-relevant fluxes and fluences and eventually used as a "flight simulator" for MPEX scenarios
- Approach: coupled multi-physics, multi-scale computational model for MPEX that can predict MPEX deuterium plasma and impurity fluxes from engineering parameters

Background on plasma-material interactions (PMI) and Material Plasma Exposure eXperiment (MPEX)

- **PMI challenge:** Multi-scale, multi-physics problem (ps to years, nm to m) where materials in a reactor divertor is not what was initially installed

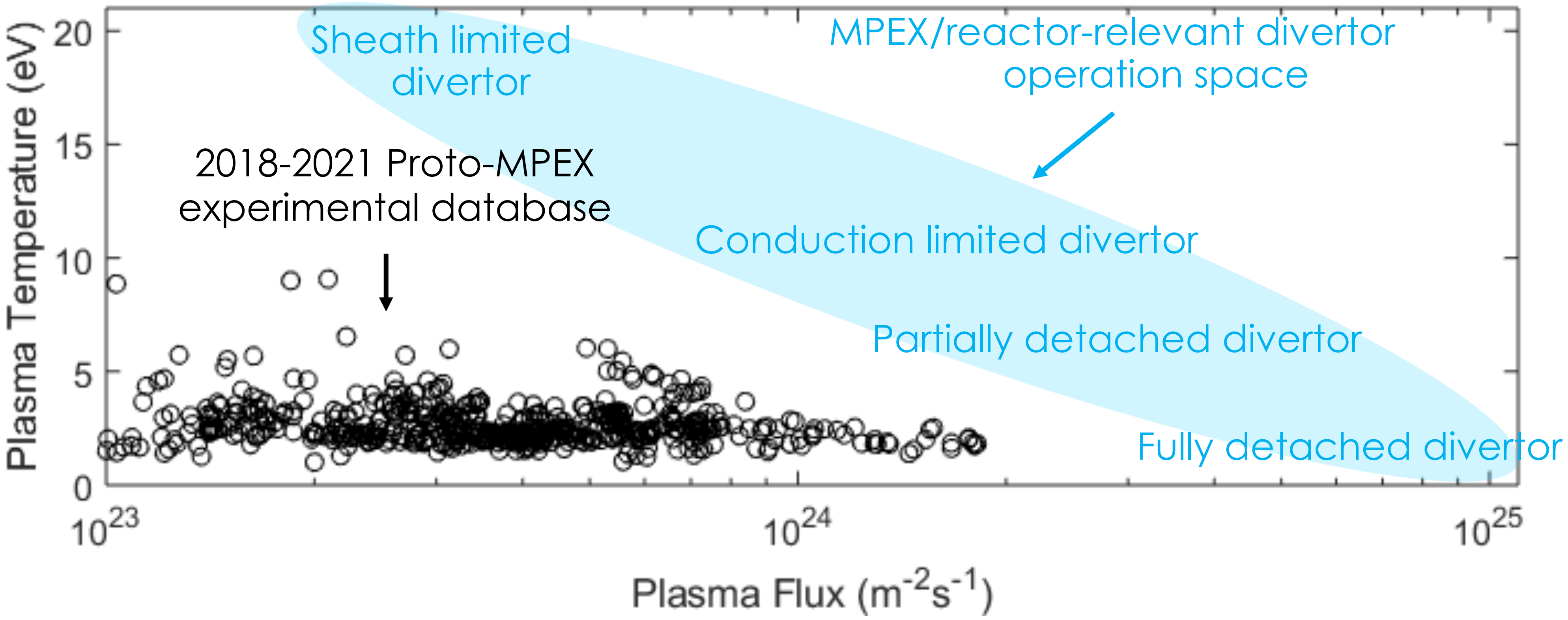


- **MPEX experiment:** linear plasma device with the goal of reactor-relevant divertor plasma fluxes(10^{25} $m^{-2}s^{-1}$) and fluences (10^{31} m^{-2}) at the target to study PMI science to study solid, liquid metals, and neutron radiated materials



Rapp, FST 2017

Challenge: model aided exploration of MPEX operation space



- Can modeling aid experimental exploration of MPEX operation space from reactor-relevant sheath limited to detached divertor regimes to accelerate commissioning from 5 to 3 years?
  - Besides hardware upgrades, models can guide and optimize the many 10's of engineering parameters used for MPEX and reduce time for experimental exploration of uninteresting plasma fluxes and temperatures for MPEX scenarios
  - Data is from Langmuir probes on-axis at target

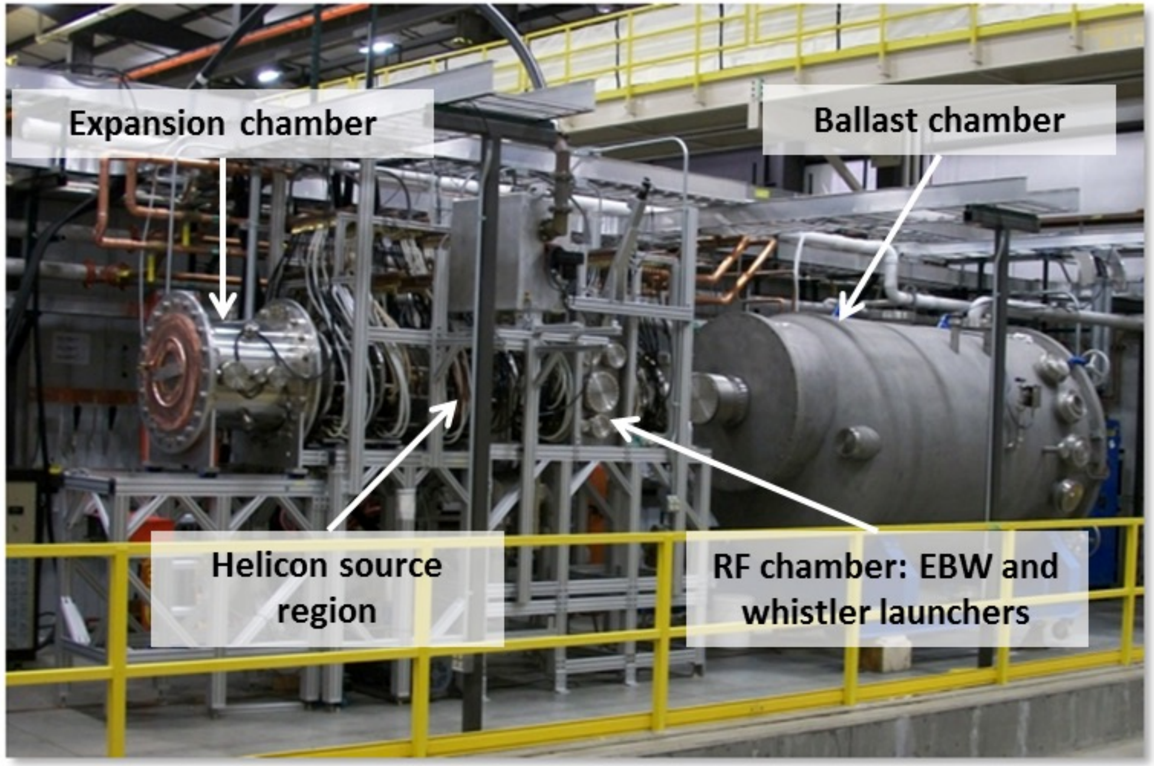
Proto-MPEX experiment (2017-2021) was used to demonstrate source and heating concept on MPEX

Input Data:

-pwr_hel, pwr_28, pwr_icrf, pg2_pres, pg3_pres, pg4_pres, axial_loc, rad_loc

Output Data:

-heat_peak_ce, heat_peak, kte, ne



Stochastic Neural Network

How to account for uncertainty and control machine learning training.

Stochastic model equation

Activation function

Noise component

$$X_t = X_0 + \int_0^t F(X_s, \theta_s)ds + \int_0^t \sigma_s dW_s$$

Control process

Control terms

$$dX_t = F(X_t, \theta_t)dt + \sigma_t dW_t, \qquad 0 \le t \le T$$

Cost function

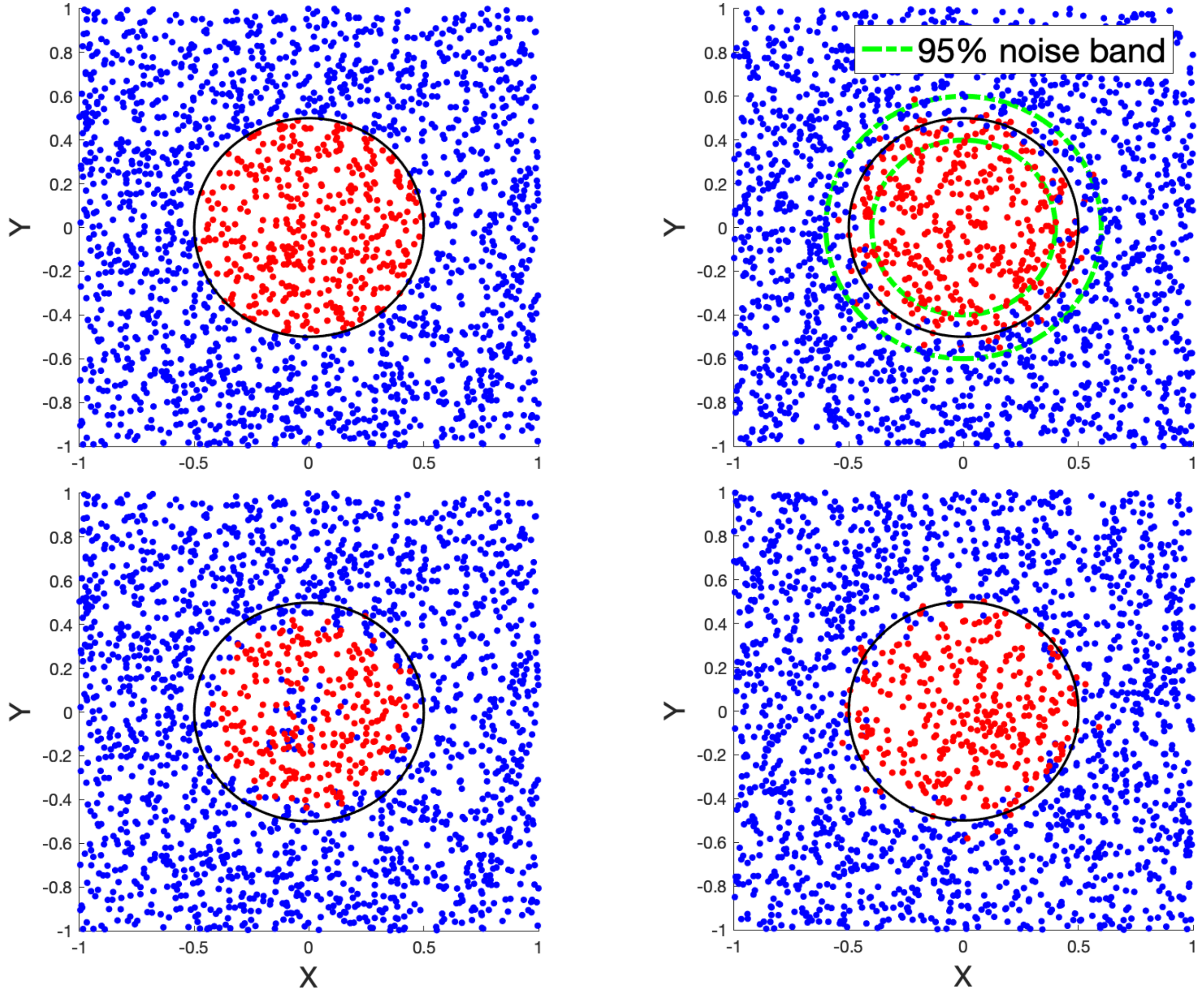
Measured data

$$J(u) := \mathbb{E}[\Phi(X_T, \Gamma)]$$

Bayesian vs Stochastic Neural Networks

Deterministic Sample

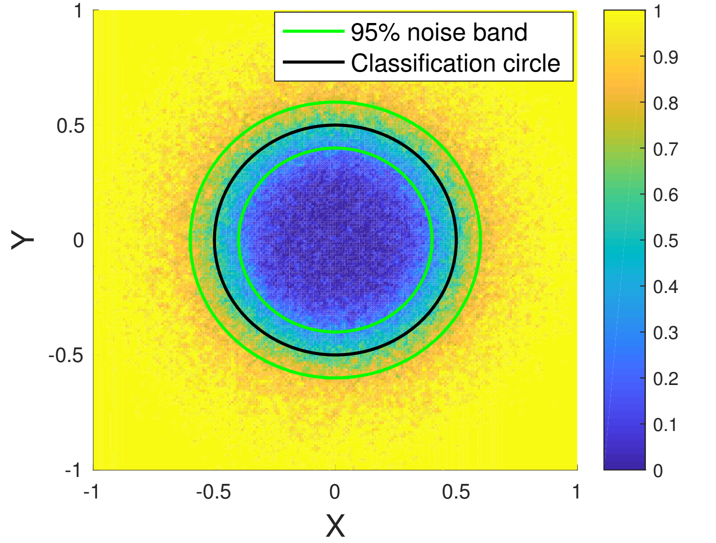
Uncertainty in Data



BNN

SNN-MP

- Robust Training
- Improved accuracy in prediction and uncertainty
- Adaptive Control



SNN-MP Weighted Prediction

OAK RIDGE National Laboratory

Archibald, Boa, Cao, & Zhang, 'Uncertainty Quantification in Deep Learning through Stochastic Maximum Principle', 2020

RL example: Robot in a maze

❖ The dynamics of the robot:

$$dX_t = v\sin\theta_t\, dt + \sigma dW_t \ ,$$
$$dY_t = v\cos\theta_t\, dt + \sigma dW_t \ ,$$

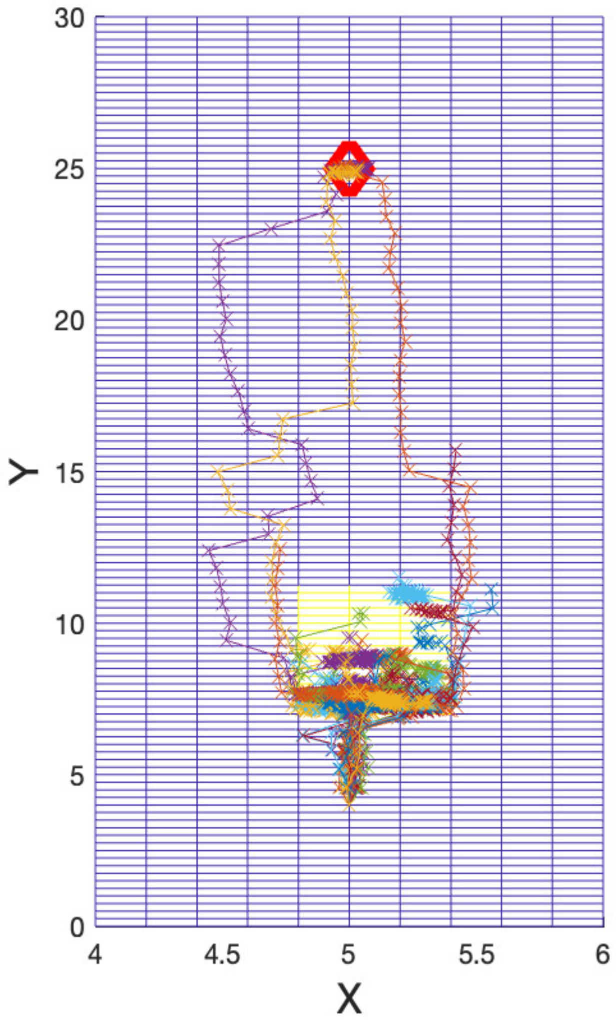
- (X_t, Y_t) gives the position of the robot.
- v is the velocity of the robot
- θ_t is the steering angle.
- $a = (v, \theta_t)$ is the control policy

❖ The cost function:

$$J(a) = \mathbb{E}[\int_0^T \lambda_x |X_T - X_0|_2^2\, dt + \Phi((X_T - X_P)^2 + (Y_T - Y_P)^2)]$$

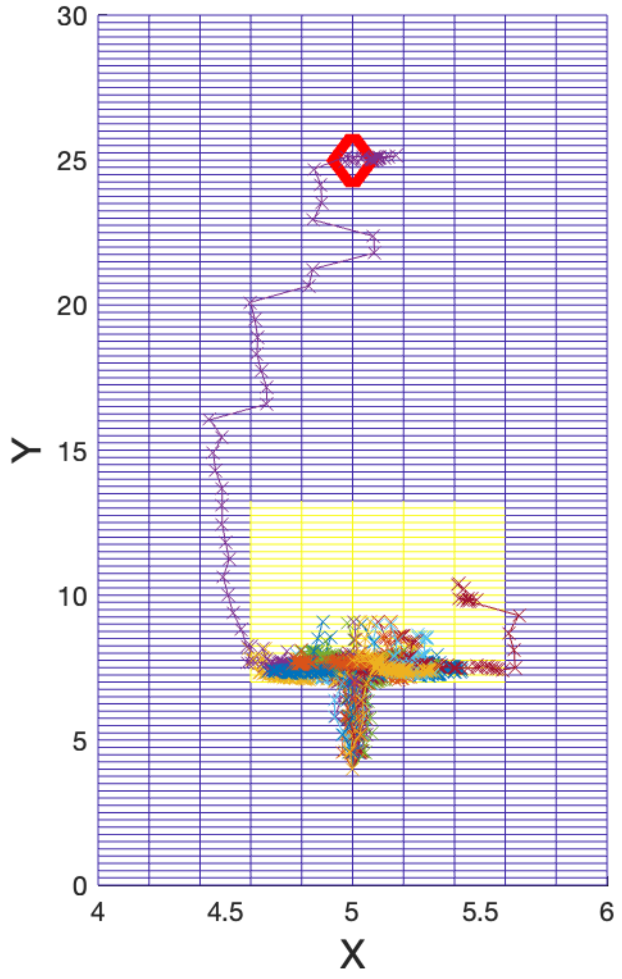
- (X_P, Y_P) is the location of the destination.
- λ_x is an unknown state-dependent cost parameter

Performance of Q-learning: a simple scenario

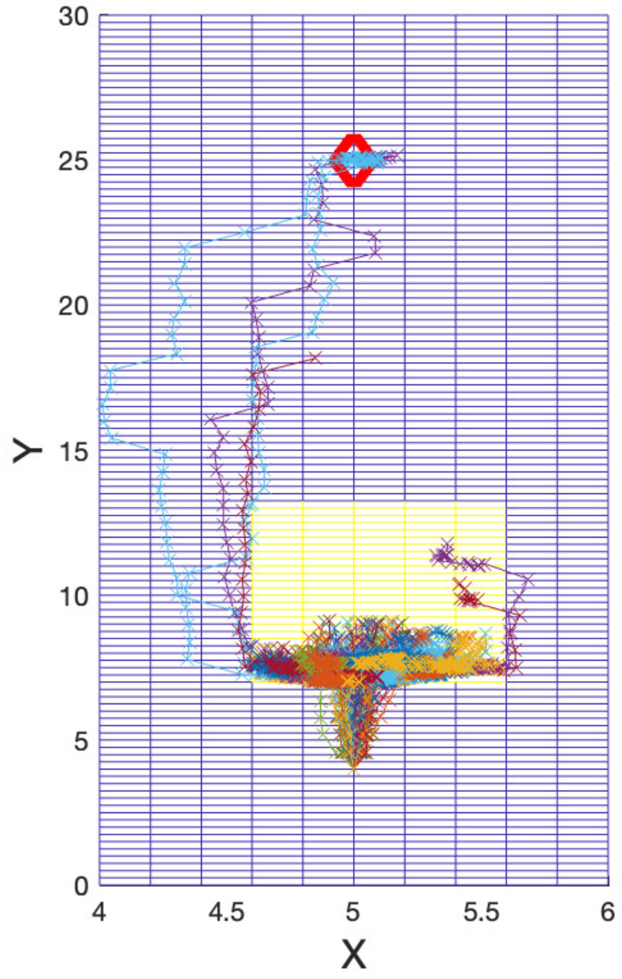


30 agent trajectories after $5{\times}10^5$ training episodes

Performance of Q-learning: a little bit more challenging

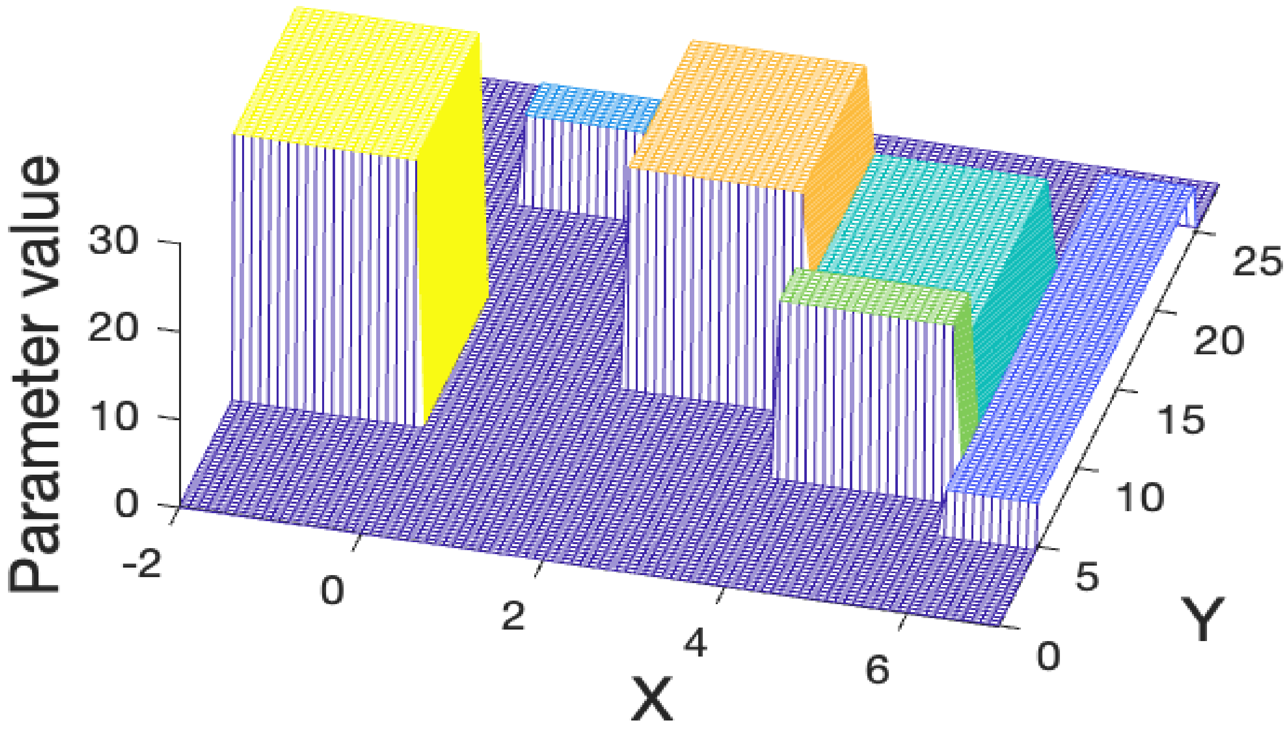


30 agent trajectories with a larger obstacle region



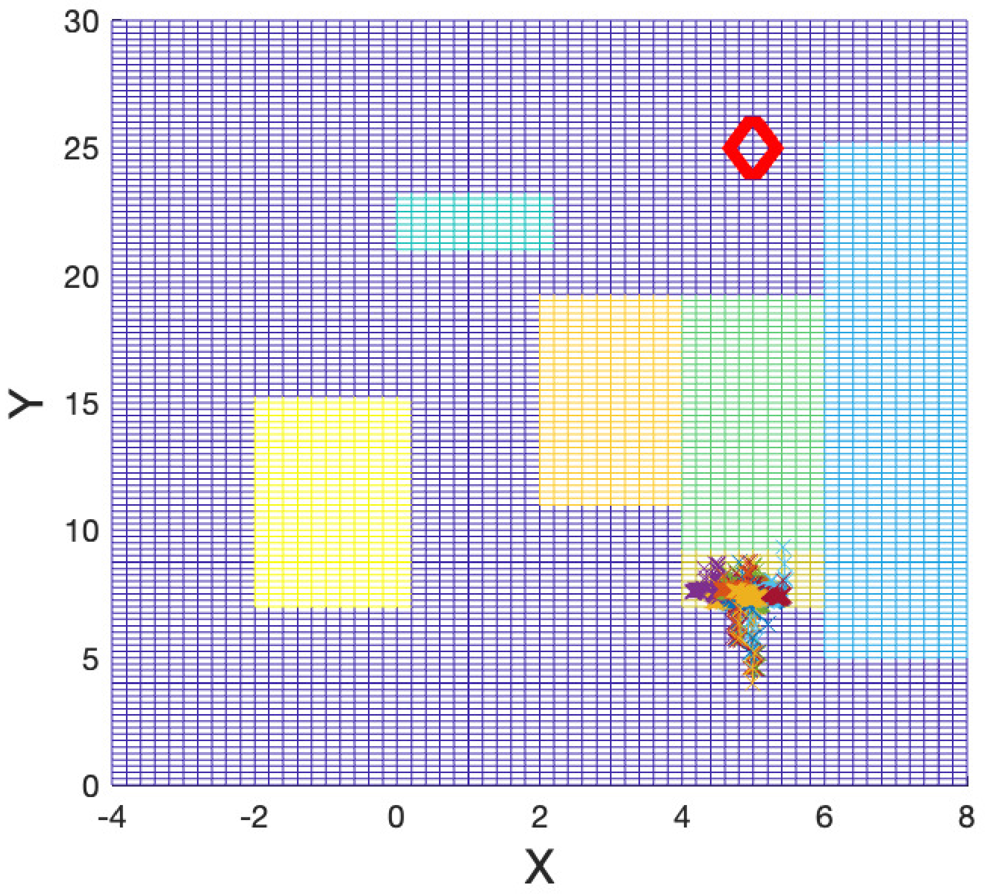
100 agent trajectories with a larger obstacle region

Performance of Q-learning: a complicated scenario



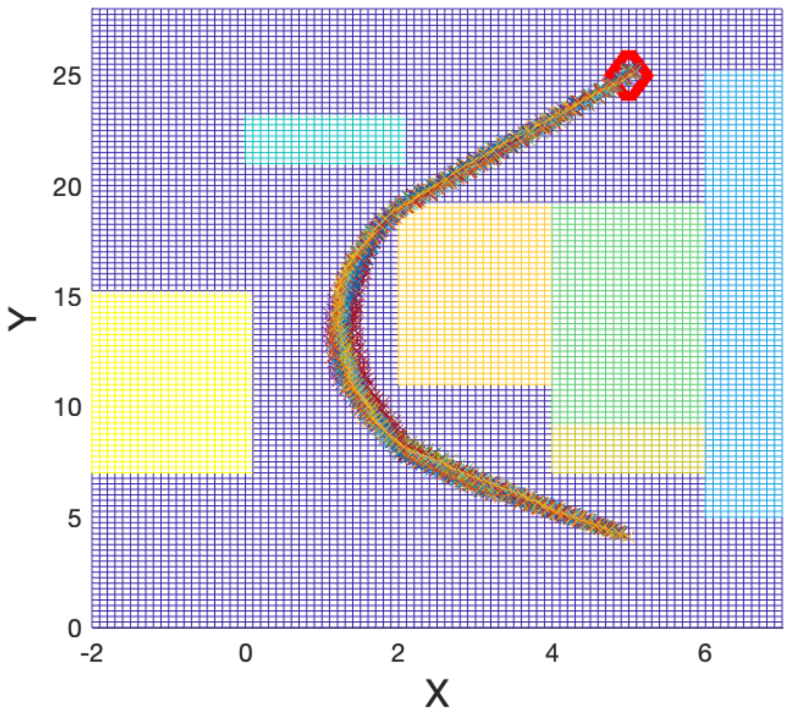
The Maze

Performance of Q-learning: a complicated scenario

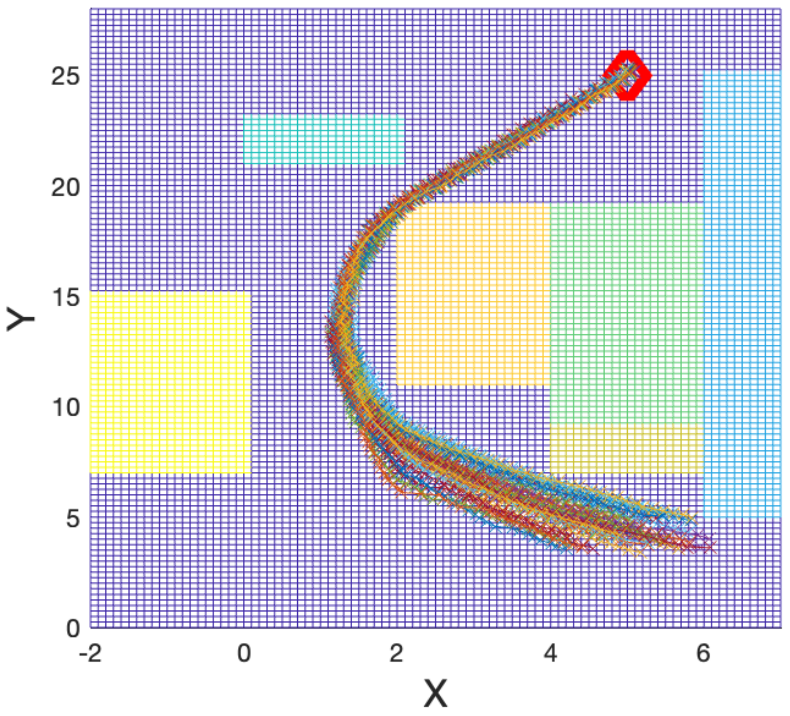


30 agent trajectories in the Maze

Performance of BAL

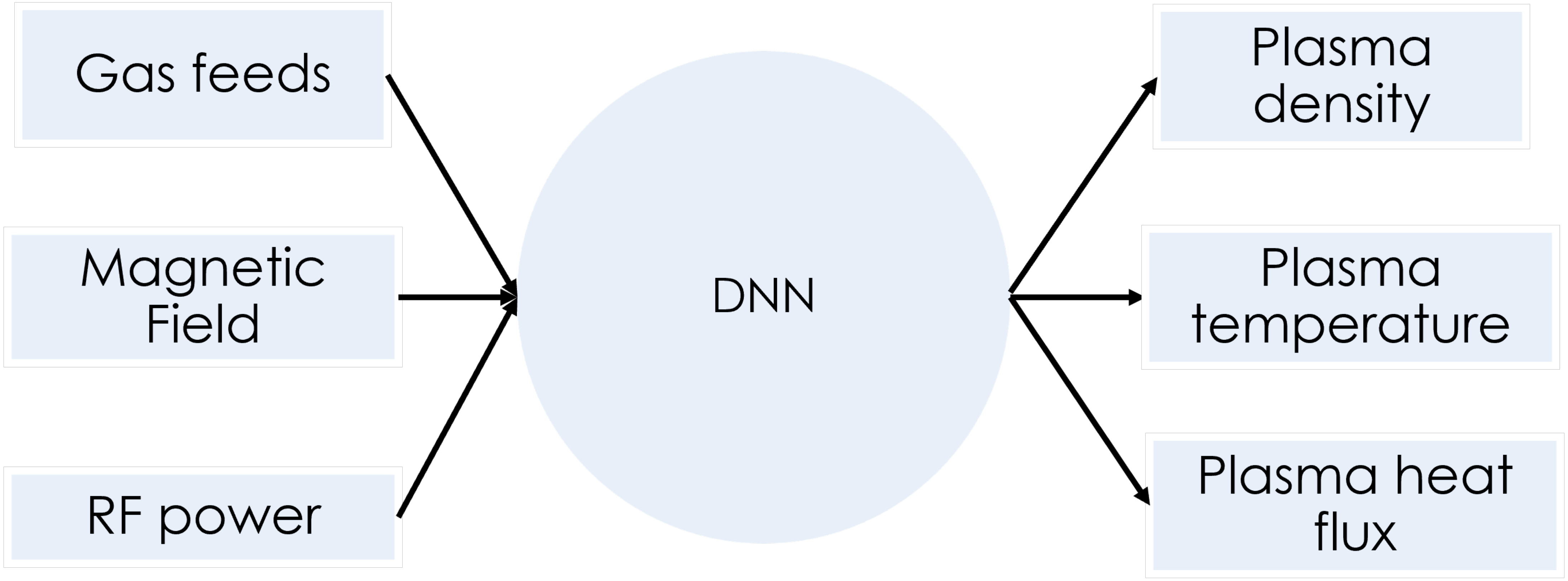


30 agent trajectories with fixed initial state



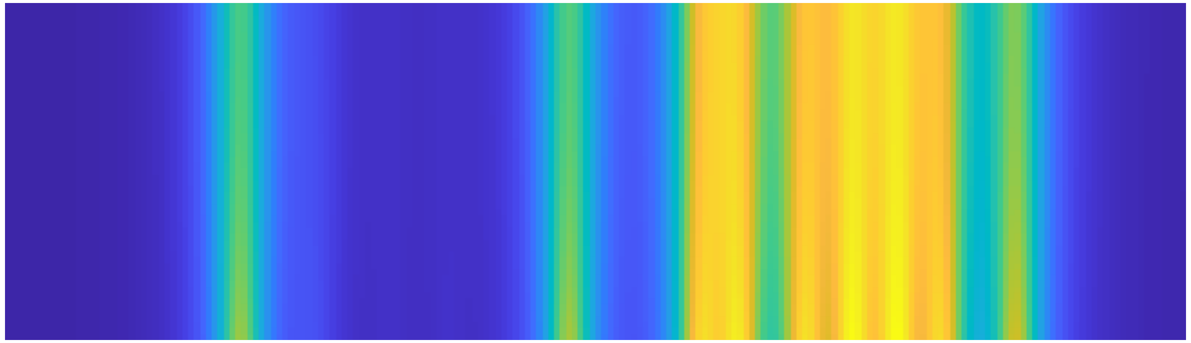
30 agent trajectories with random initial state

MPEX ML

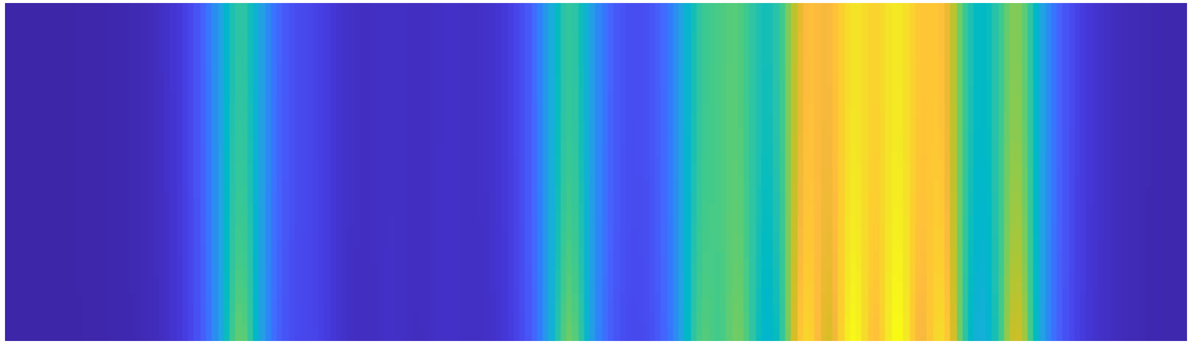

Gas feeds
Magnetic Field
RF power
DNN
Plasma density
Plasma temperature
Plasma heat flux

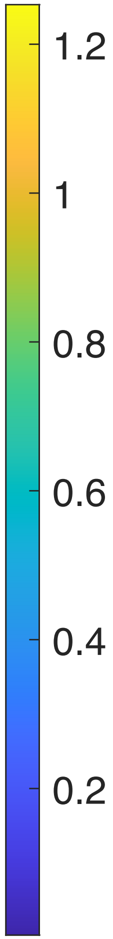
MPEX ML Magnetic Field

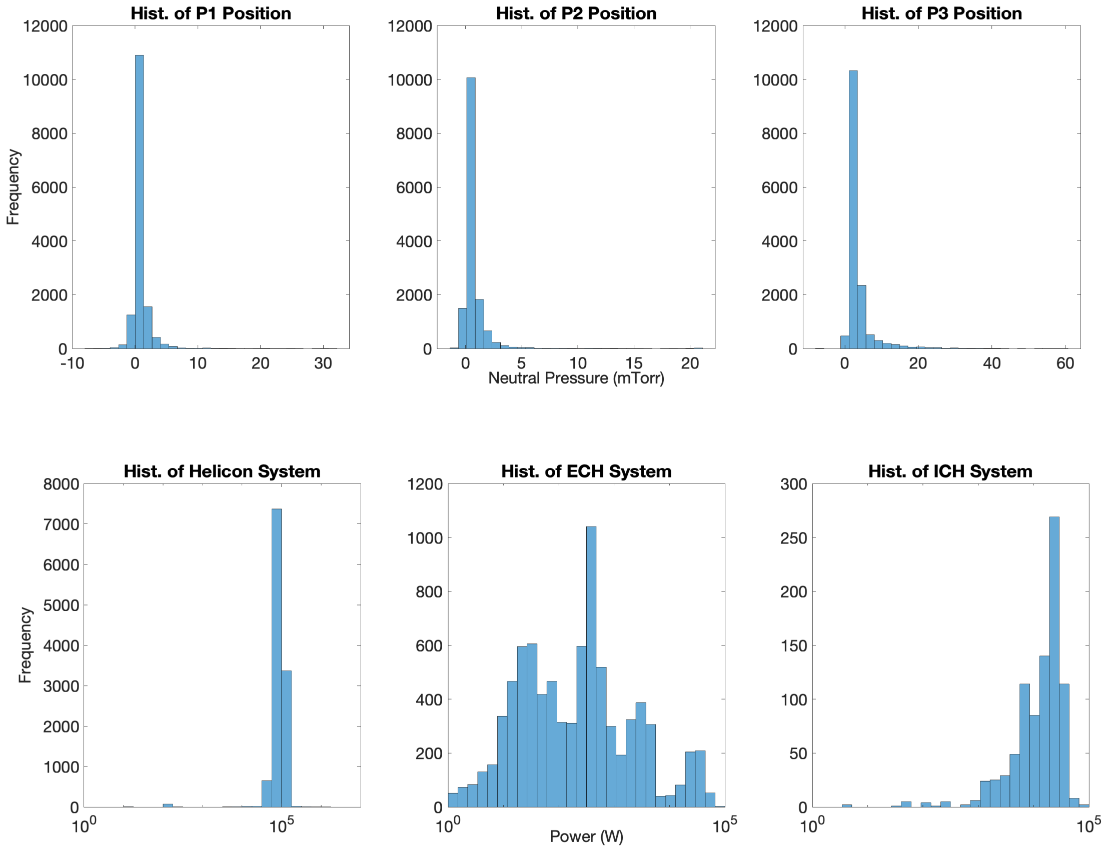
Sample Shot Magnetic Field



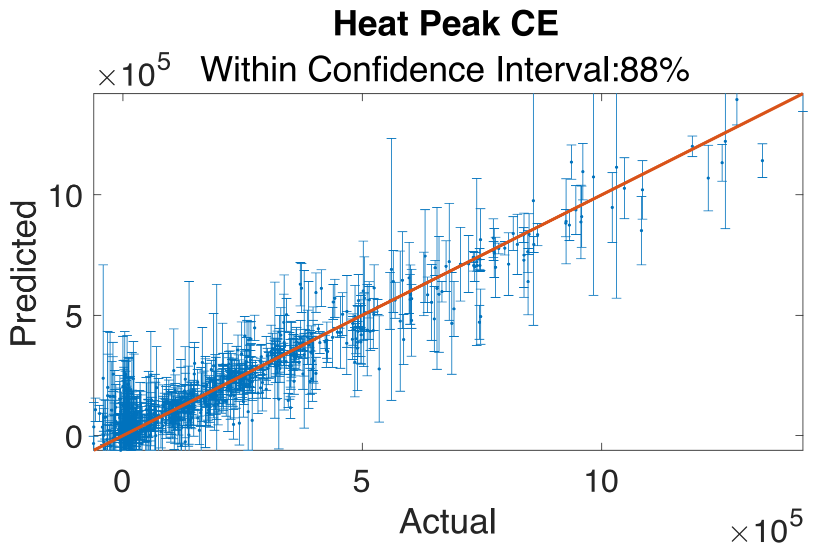
Approximation using two Principal Components

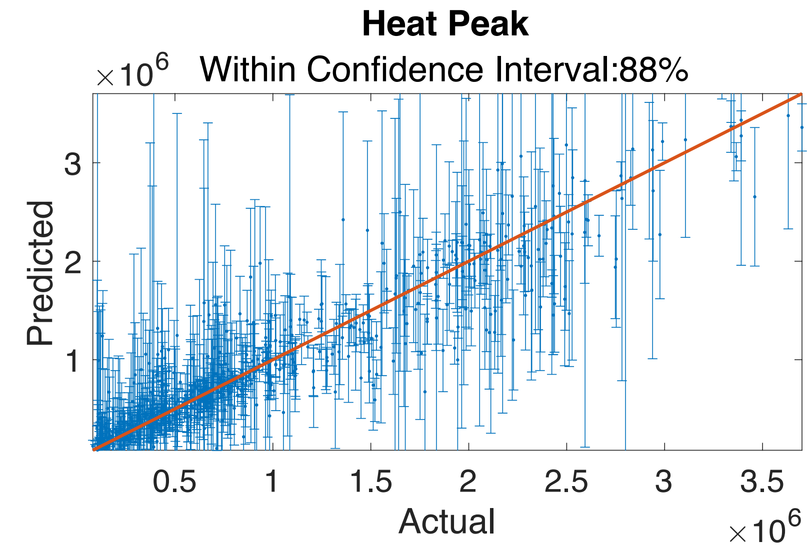


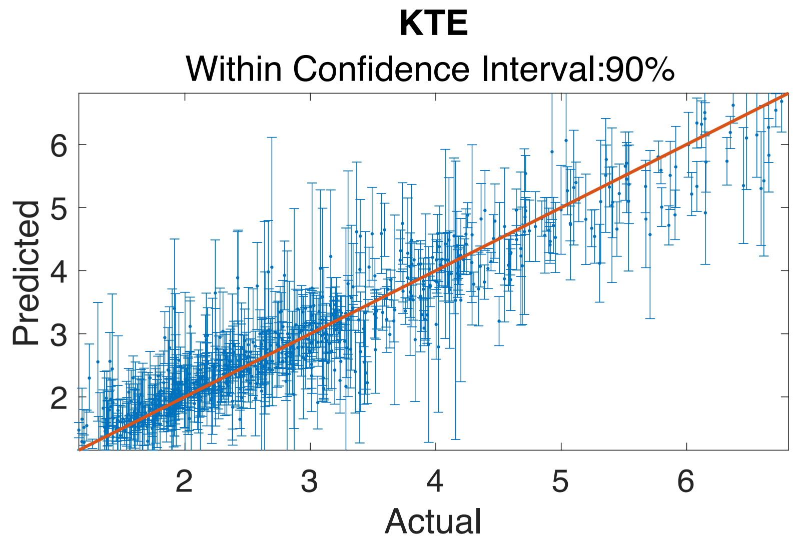


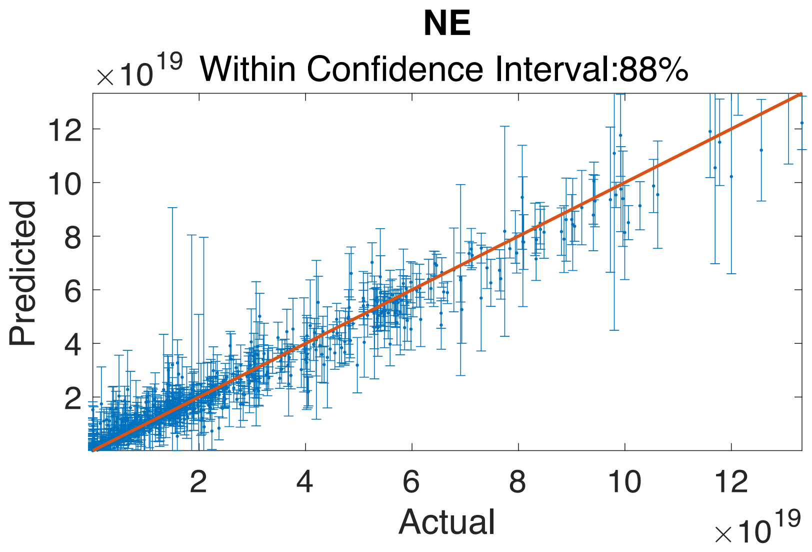


SNN Results

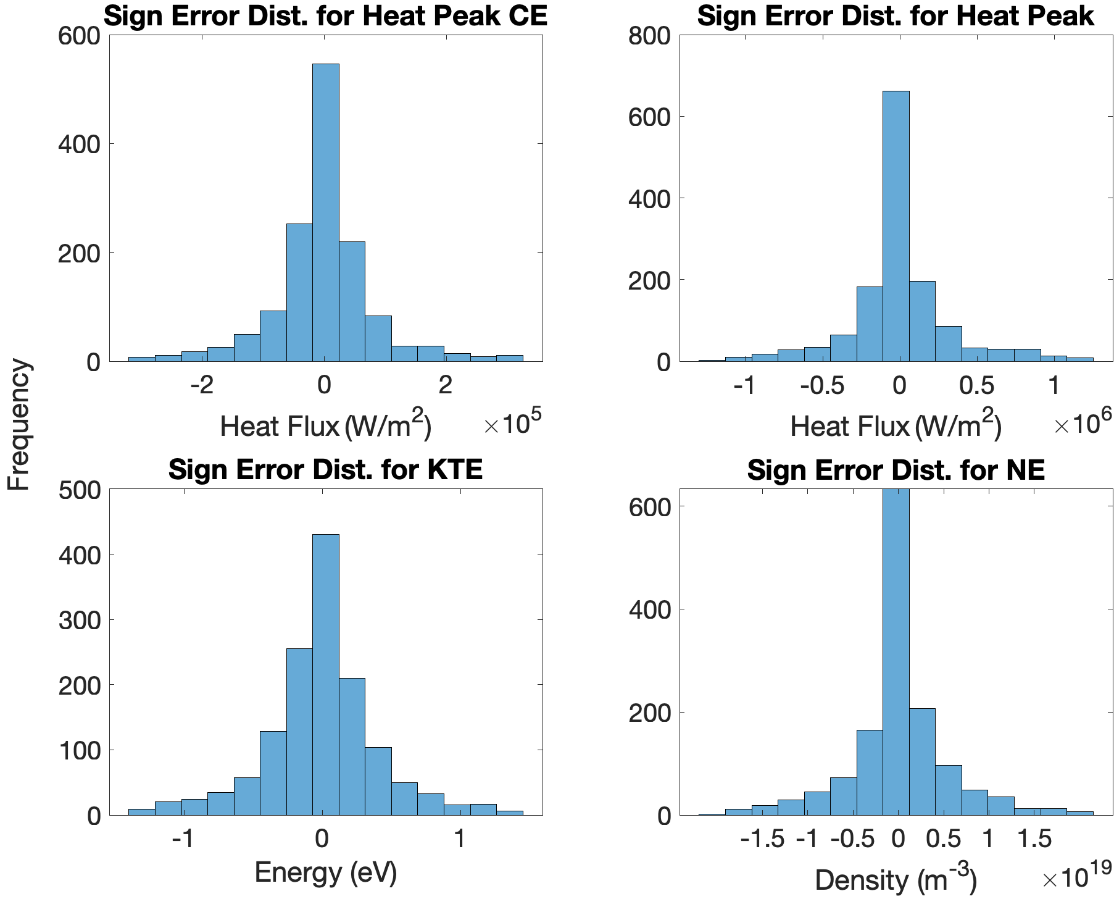

Heat Peak CE
Within Confidence Interval:88%
×10^5
Predicted
Actual
×10^5
0
5
10

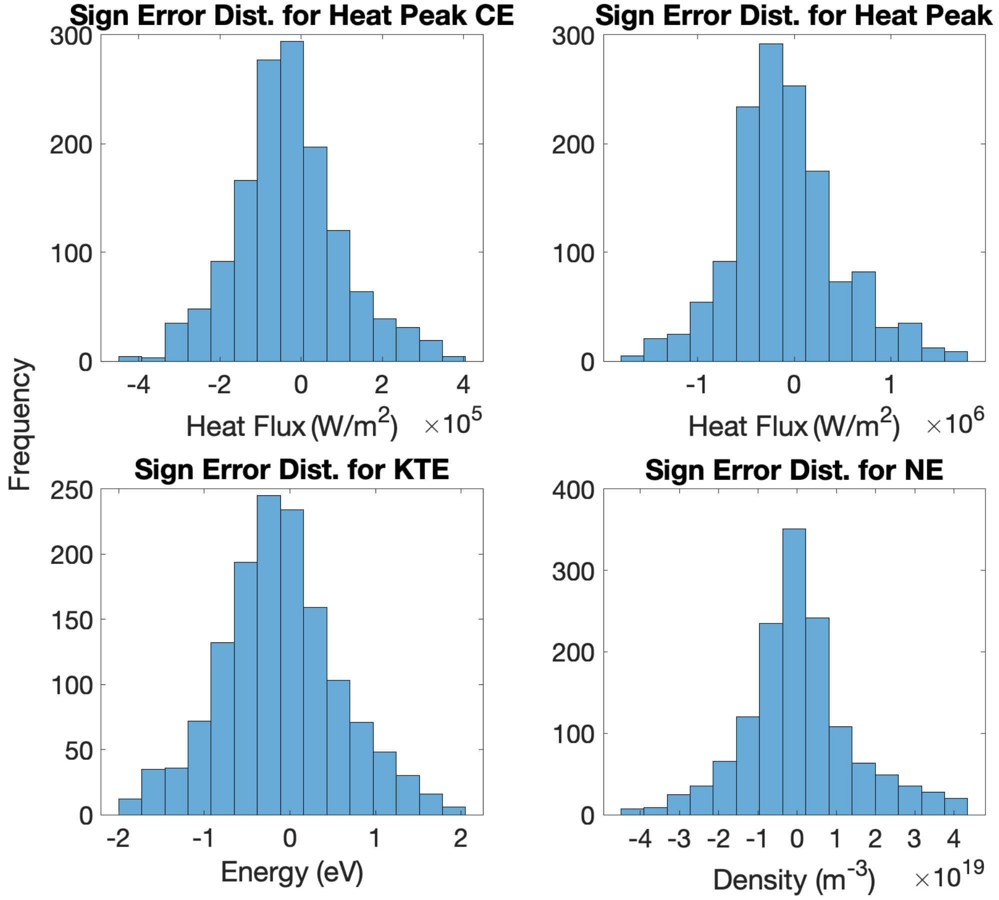

Heat Peak
Within Confidence Interval:88%
×10^6
Predicted
Actual
×10^6
1
2
3
0.5
1.5
2.5
3.5


KTE
Within Confidence Interval:90%
Predicted
Actual
2
3
4
5
6

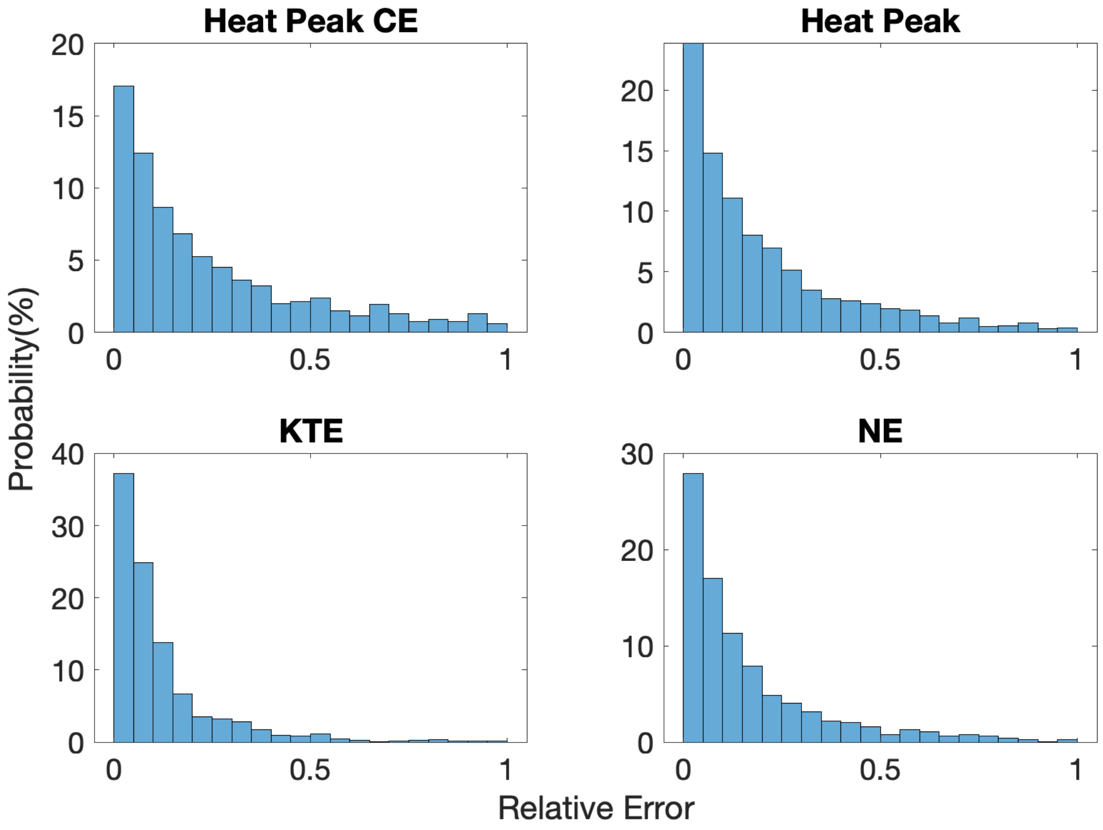

NE
Within Confidence Interval:88%
×10^19
Predicted
Actual
×10^19
2
4
6
8
10
12

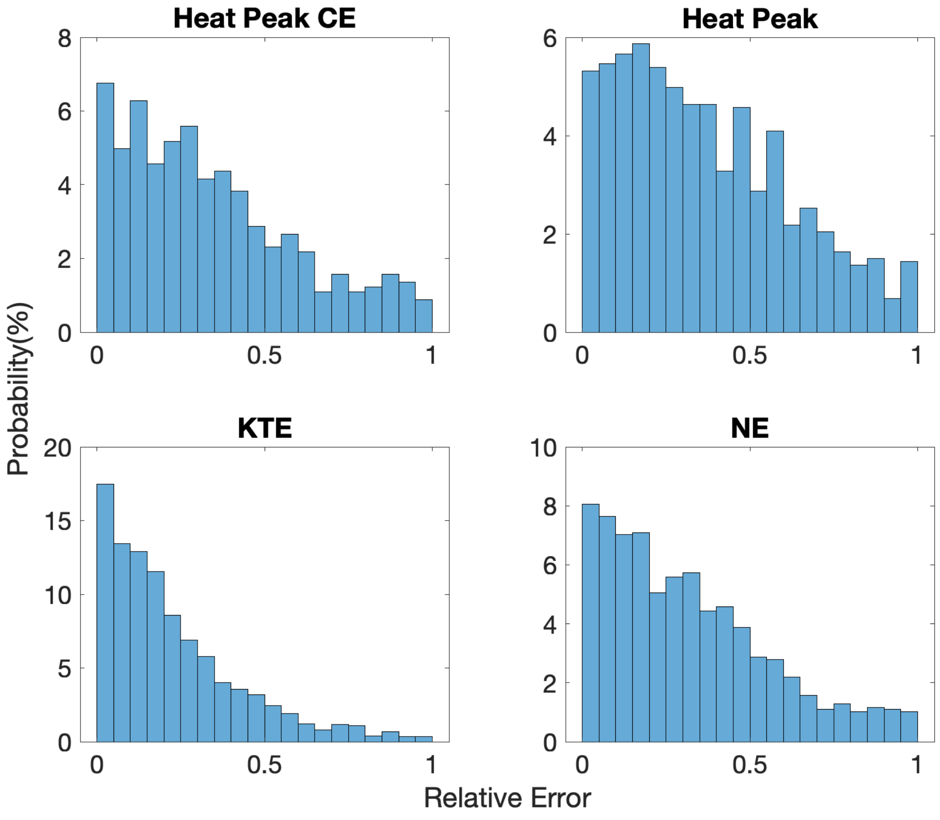
SNN vs BNN


Sign Error Dist. for Heat Peak CE
Heat Flux (W/m^2) ×10^5
Sign Error Dist. for Heat Peak
Heat Flux (W/m^2) ×10^6
Frequency
Sign Error Dist. for KTE
Energy (eV)
Sign Error Dist. for NE
Density (m^-3) ×10^19


Sign Error Dist. for Heat Peak CE
Heat Flux (W/m^2) ×10^5
Sign Error Dist. for Heat Peak
Heat Flux (W/m^2) ×10^6
Frequency
Sign Error Dist. for KTE
Energy (eV)
Sign Error Dist. for NE
Density (m^-3) ×10^19

SNN vs BNN


Heat Peak CE
Heat Peak
KTE
NE
Probability(%)
Relative Error


Heat Peak CE
Heat Peak
KTE
NE
Probability(%)
Relative Error