AVALANCHE

A Data-Driven Model for the Prediction of Field Emission Current from Broad-Area Electrodes

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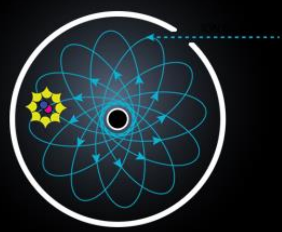
WIKS SLOTT - Sweden

Orbitron Introduction

Orbitrap Technology



Orbitrap-type geometries trap ions in self-intersecting, elliptical orbits with high-voltage electrostatics.

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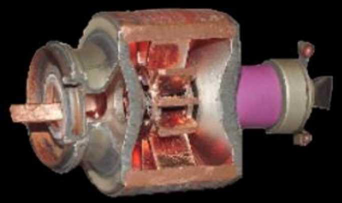
Magnetron Technology



Smooth-bore magnetron architectures trap electrons in cycloidal orbits with magnetic fields.

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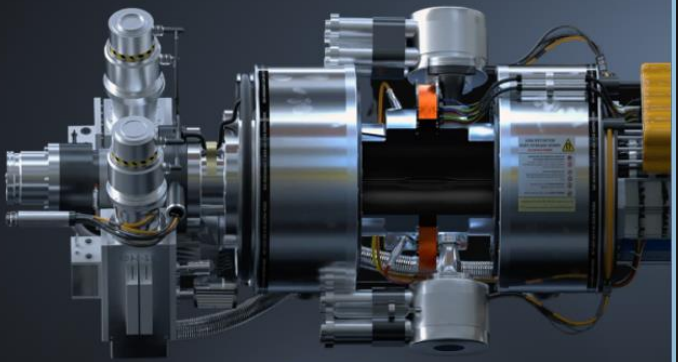
Orbitron

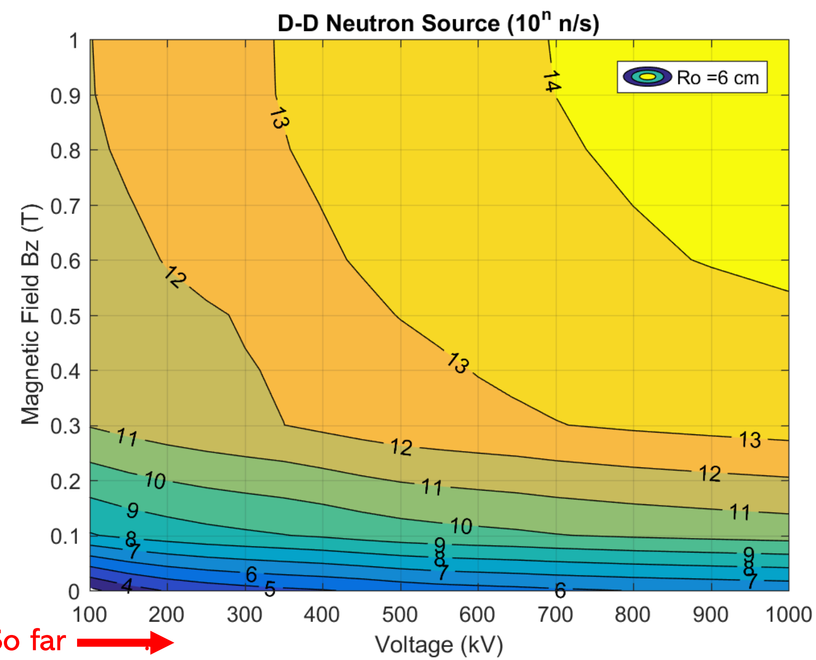
Fusion Microreactor



Combining an orbitrap and magnetron, increasing voltage up 100's of kV, operating in a deep vacuum conditions co-confines high-speed ions & electrons for useful fusion.

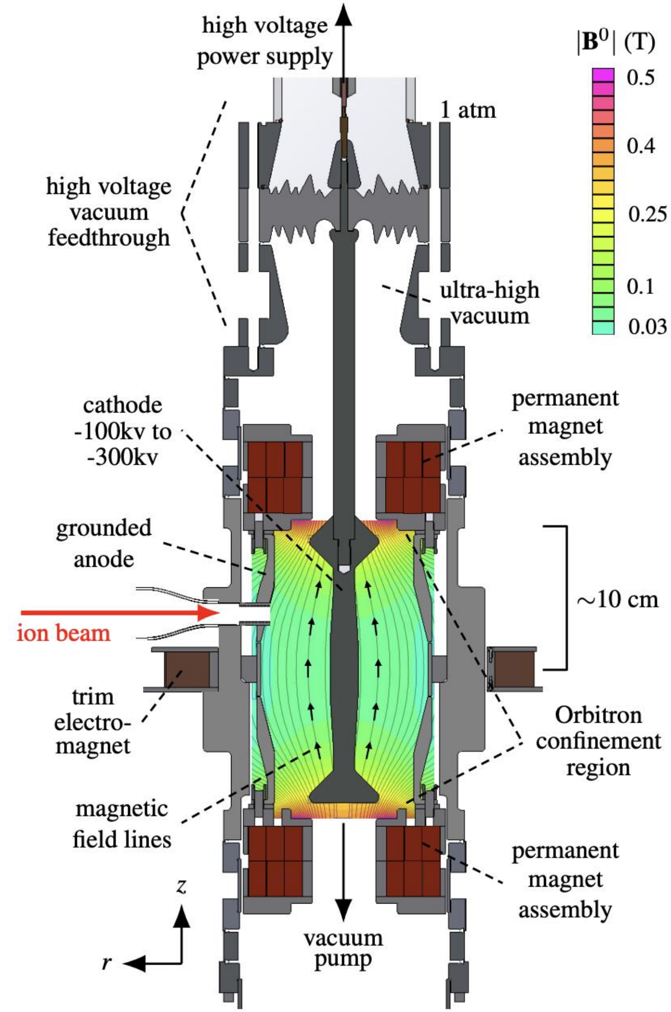
High Voltage Program

- Three working fusion machines with voltages ranging from 30kV to 200kV.
- Next generation with 300kV capability.



So far →

Near future →



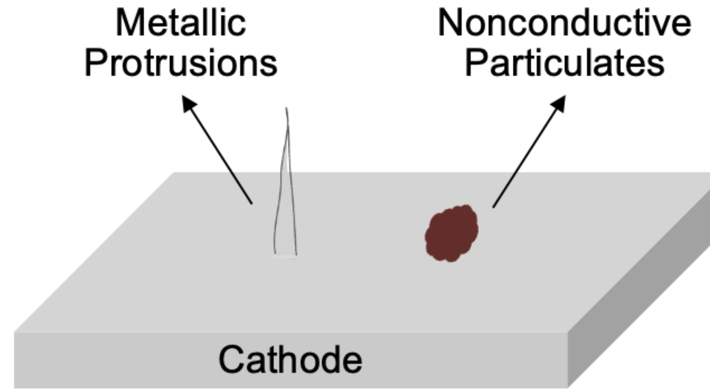
A Predictive Model of Field Emission

Conventional FE Models

- Murphy-Good Formula

$$J = C_1 \frac{(\beta E)^2}{\phi\, t(y)} \exp\left(-\frac{C_2\, \phi^{\frac{3}{2}}\, v(y)}{\beta E}\right)$$

$$I = \sum_{i=1}^{N} A_i\, C_1 \frac{(\beta_i E_i)^2}{\phi_i} \exp\left(-\frac{C_2\, \phi_i^{\frac{3}{2}}}{\beta_i E_i}\right)$$



- Constrained by lack of data on the distribution and geometry of emitters.
- Predictions become more challenging with non-uniform electric field distribution at the cathode surface.
- Consequently, FE formulations are frequently calibrated using current–voltage data after test → not usually a good predictive model.

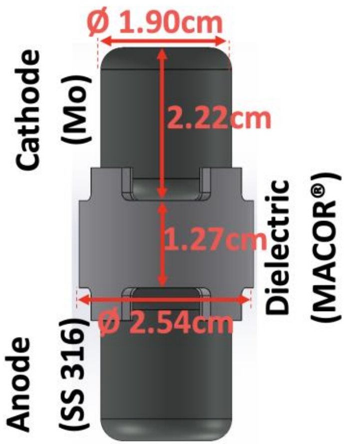
Big data to the rescue? Maybe

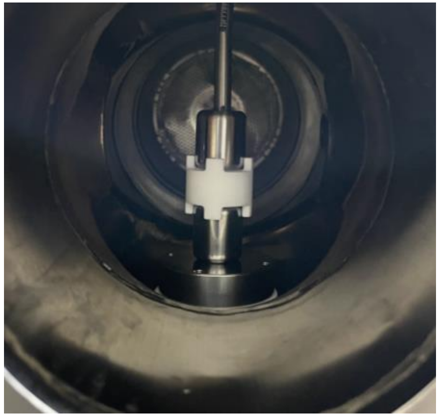
- Many research groups, companies, and national labs have generated a significant amount of data.
- The high voltage group at Avalanche Energy has generated over 850 hours of raw experimental data over the past three years.
- Can we pair these data with other information we have, for example:
    - Electric field simulation,
    - Surface microscopy,
    - Material and the surface area,
    - Vacuum pressure,
    - ….

- 1st Objective: Assess the feasibility of training a machine learning model to predict the stable field emission current

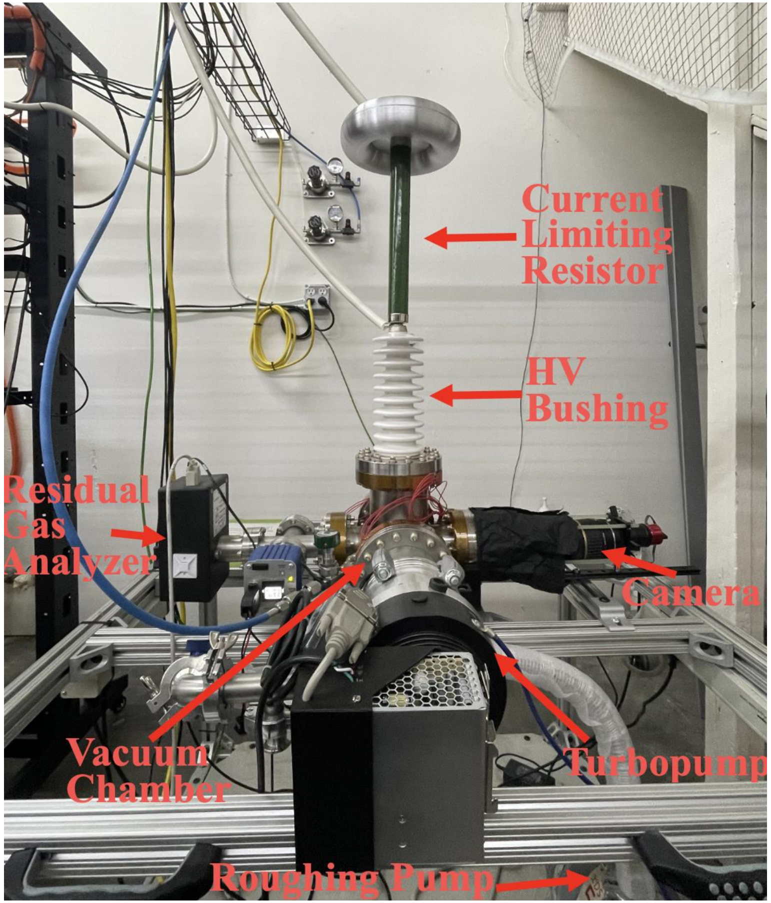
Experimental Setup

- **-80 kV** Power Supply
- High Vacuum ($< 10^{-8}\ Torr$)
- Measurements include:
    - Power supply voltage and current
    - Anode current
    - X-ray Emission





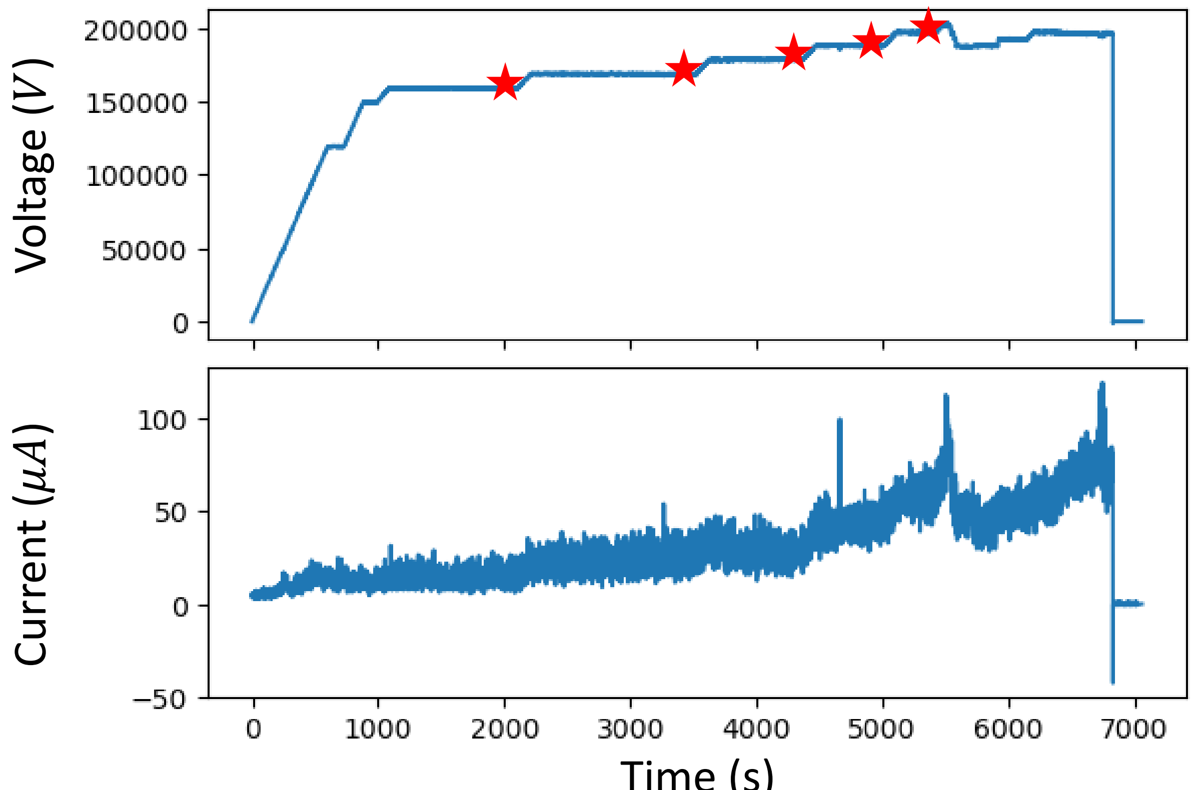
The assembly of test samples.



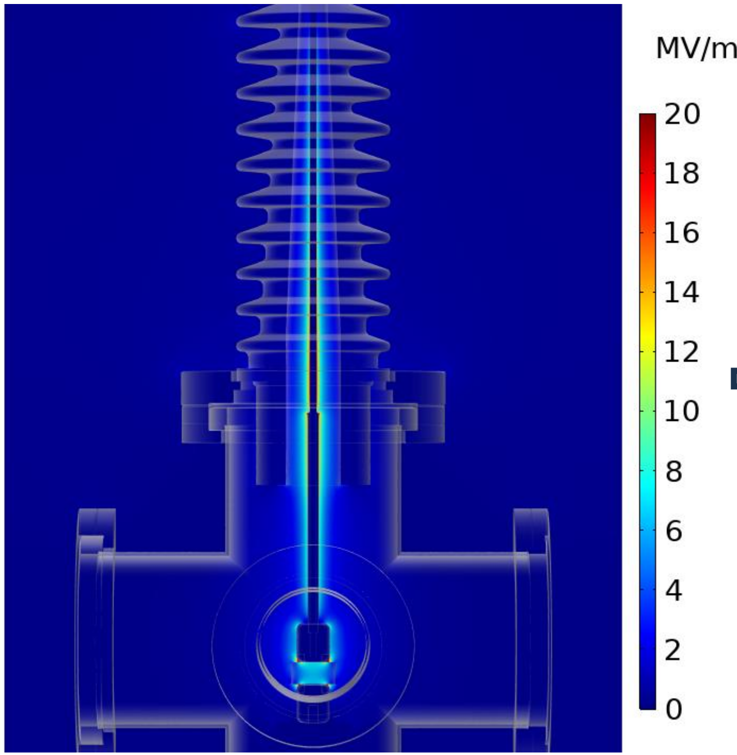
High voltage test setup

Data-Driven Approach to Field Emission

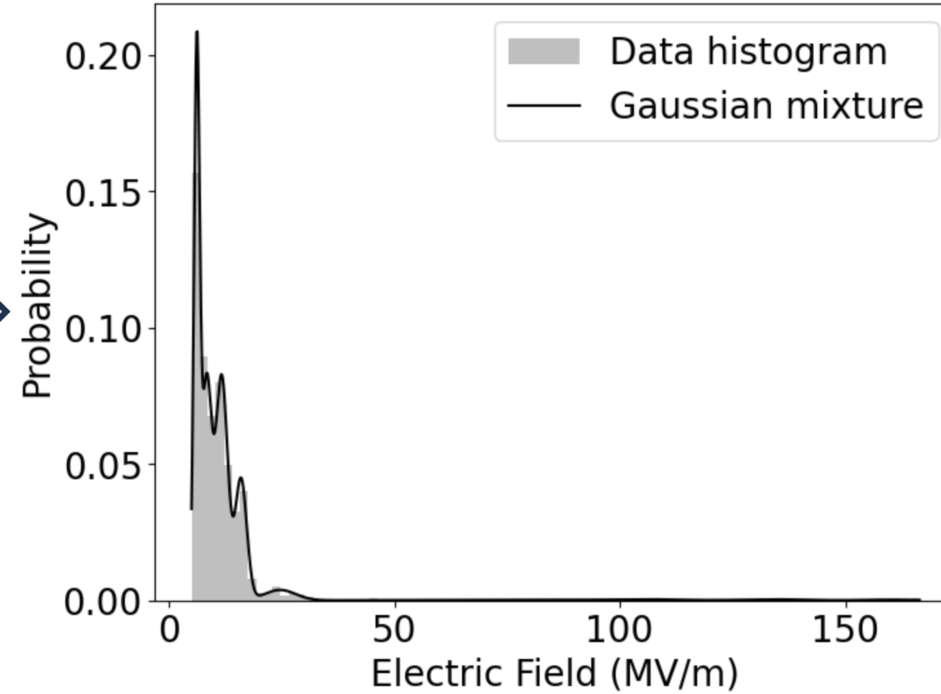
- Extracting conditioned data points over 259 hours of experimental data



Electrostatic Field Simulation



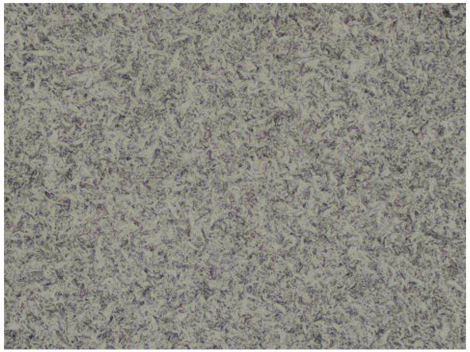
The electric field distribution.



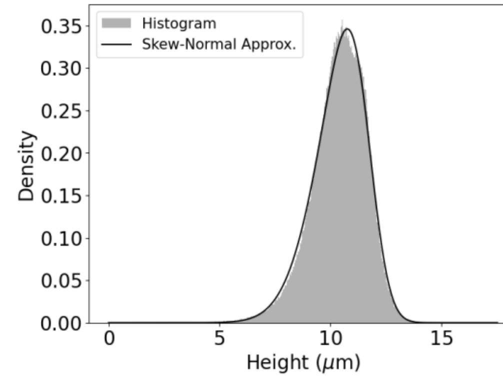
Probability distribution of electric field at the surface of cathode.

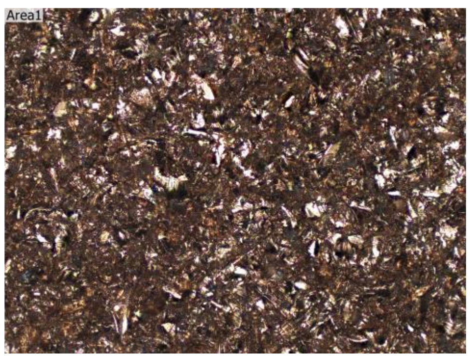
M. Borghei, R. Langtry, A data-driven model for the field emission from broad-area electrodes, Results in Physics, Volume 66, 2024, 107999, ISSN 2211-3797.

Surface Profilometry

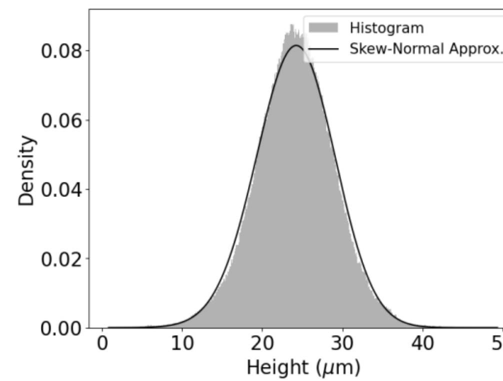


Polished molybdenum.





Grit Blasted Copper.

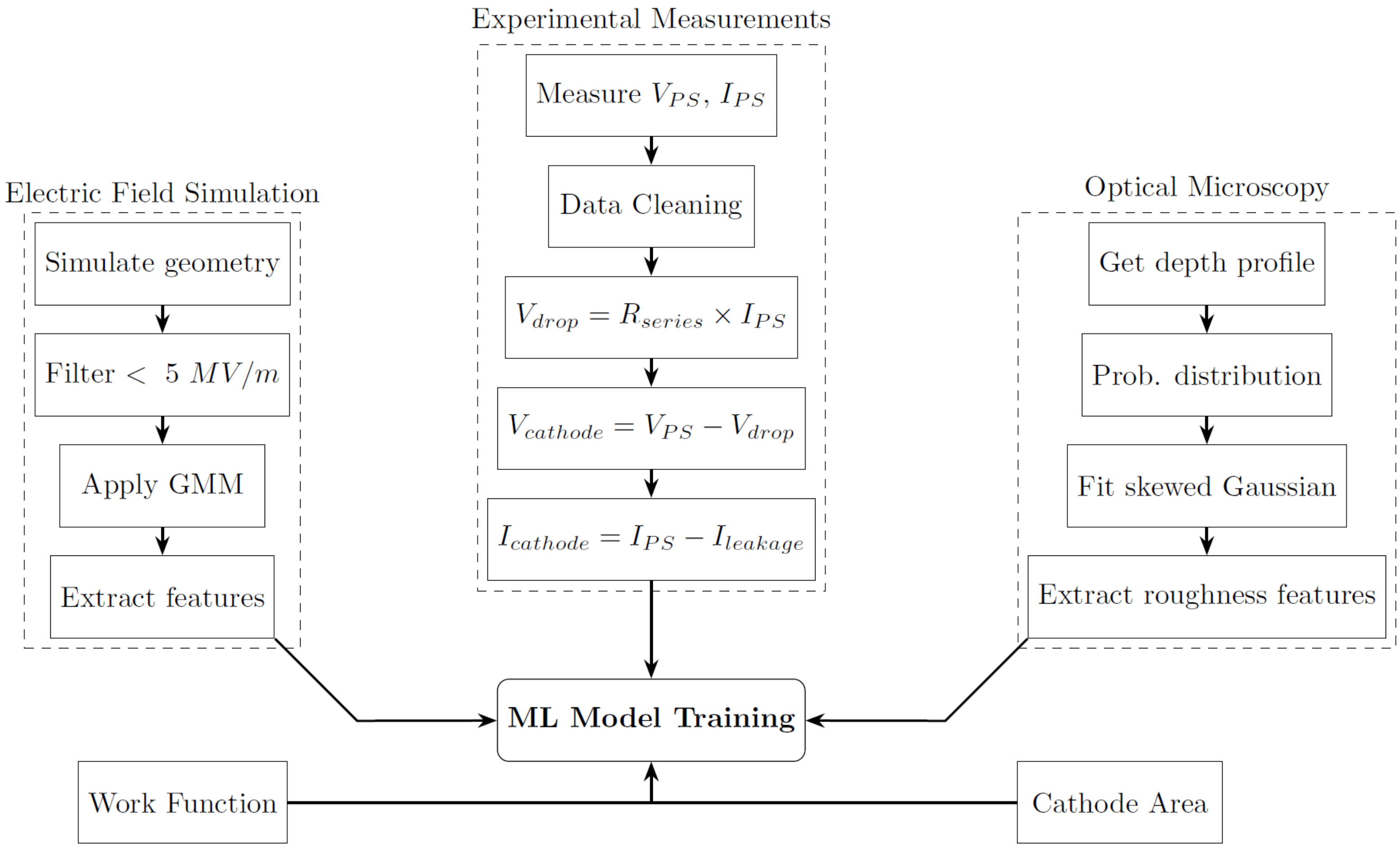


10x Magnification.

The probability distribution of surface depth.

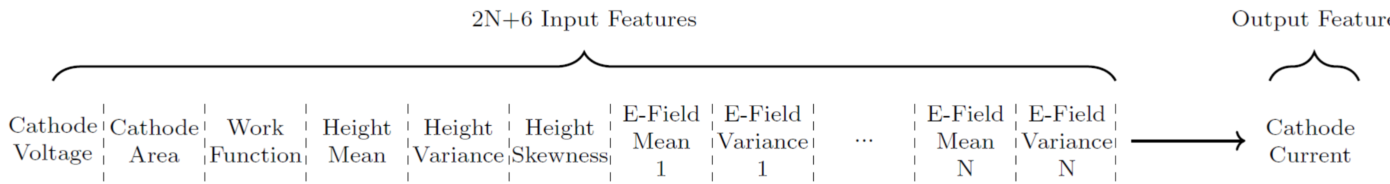
M. Borghei, R. Langtry, A data-driven model for the field emission from broad-area electrodes, Results in Physics, Volume 66, 2024, 107999, ISSN 2211-3797, https://doi.org/10.1016/j.rinp.2024.107999.

Data-Driven Approach to Field Emission

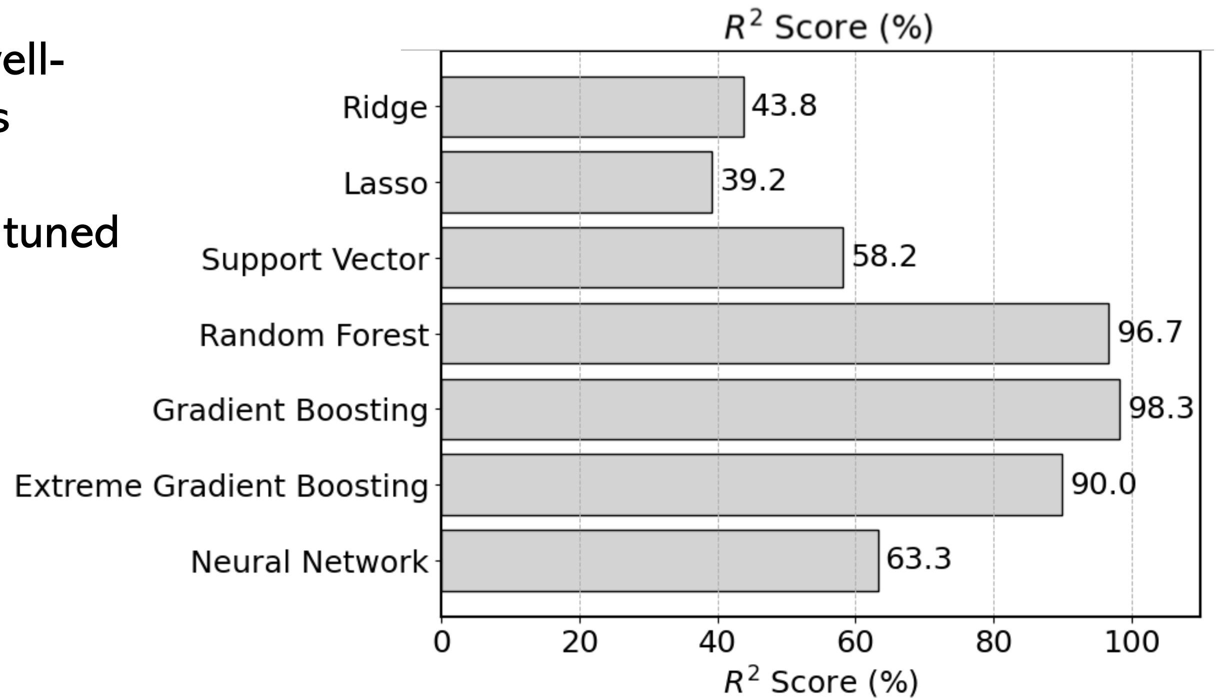


Benchmarking different ML Models

Data Structure:



- Cross-validated well-known ML models
- Hyperparameters tuned using Bayesian optimization



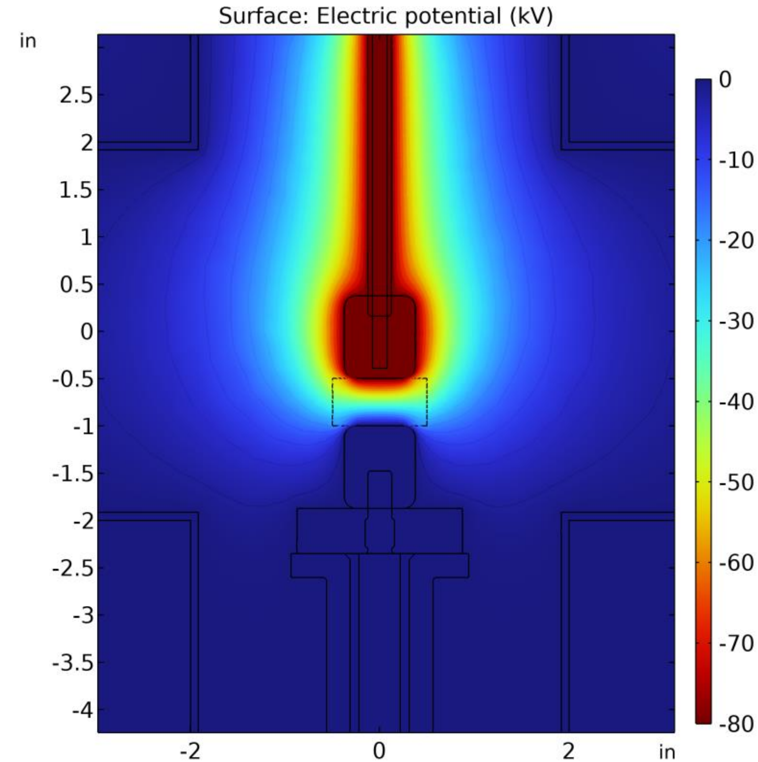
Takeaways

- A machine learning model was built based on extracted data from >250 hours of testing,.
- Ensemble learning models work great! A prediction accuracy of >98% was achieved.
- It tells us that for a specific geometry, you can predict stable field emission current
- What this first model does not tell us are:
    - Changing one geometry to another
    - The variations of I-V curve during conditioning
    - The duration of conditioning
    - Prediction of breakdown events
    - Many other things…

Predictive Model of Field Emission: Temporal I-V Curve

Various Configurations

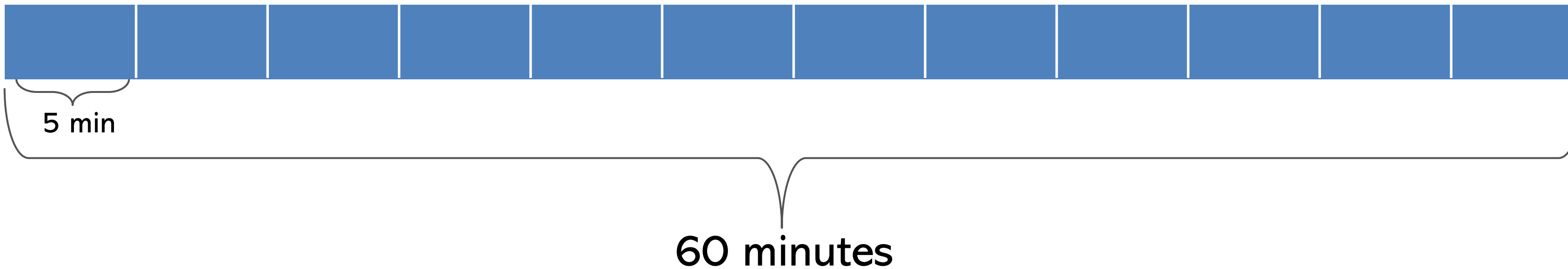
- 546 tests with 850 hours of data are available
- Using 20% of the data in four configurations



An Example of the electrodes configuration

Data Preprocessing: Features

- Each test is segmented into subtests with fixed width

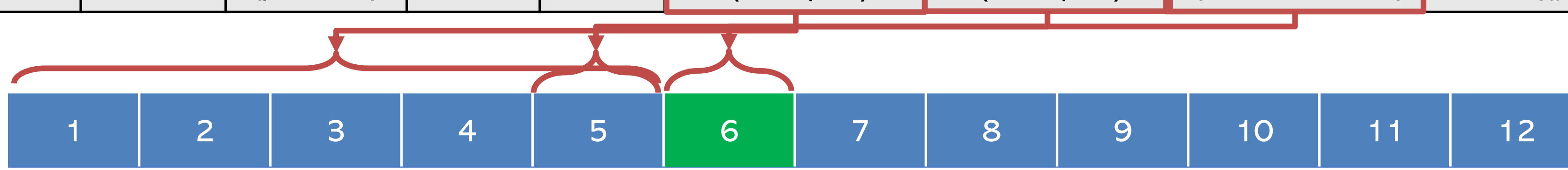


- Fixed properties

Test ID	Power Supply	R_{series}	Cathode Area	Work Function	Surface Finish

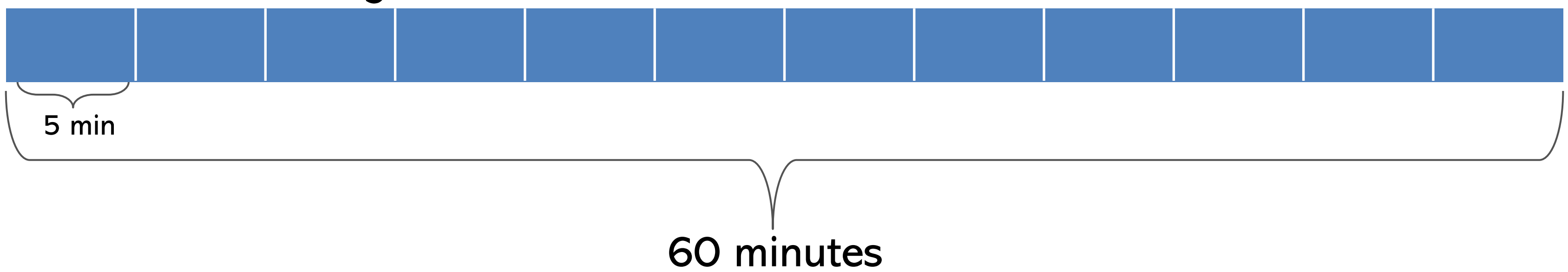
- Properties the change for each subtest

Segment ID	Elapsed Time	Mass flow (pressure)	Energy	Peak Power	V_{prior} and I_{prior} $(\max, \mu, \sigma)$	V_{prev} and I_{prev} (max, μ, σ)	V_{curr} (min, max, μ, σ)	E-Field Scaled to V_{curr}



Data Preprocessing: Targets

- Each test is segmented into subtests with fixed width



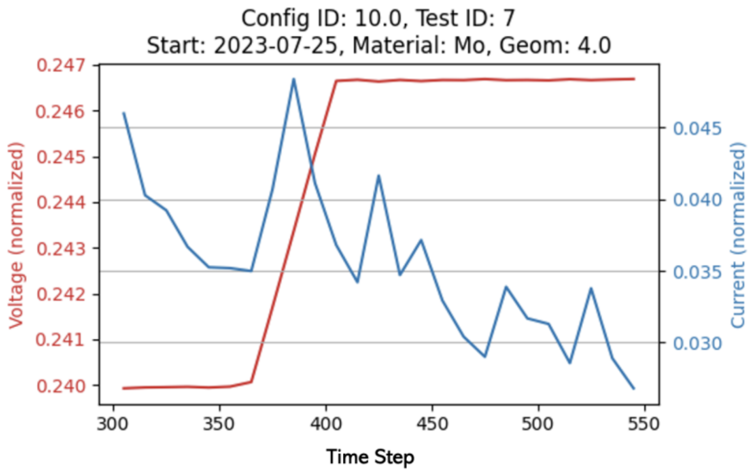
- Targets for the learning model.

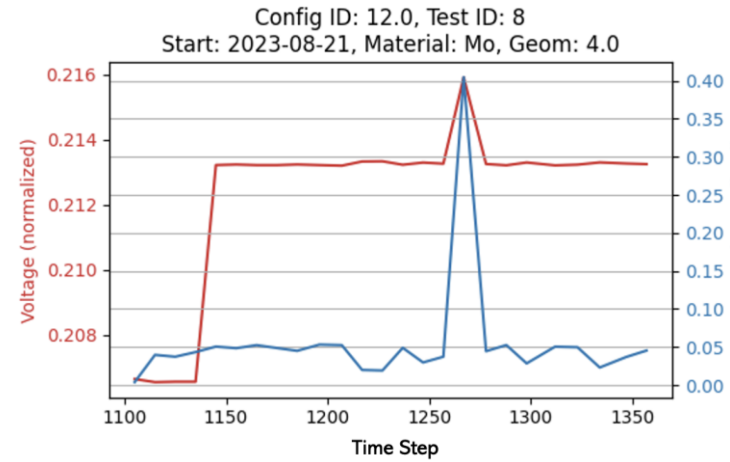
I_{max}	I_{min}	I_{mean}	$I_{std\ dev}$	I_{skew}	$I_{V_{max}}$	$t_{I_{max}}$	$t_{V_{max}}$	dI/dV	$Q_{segment}$

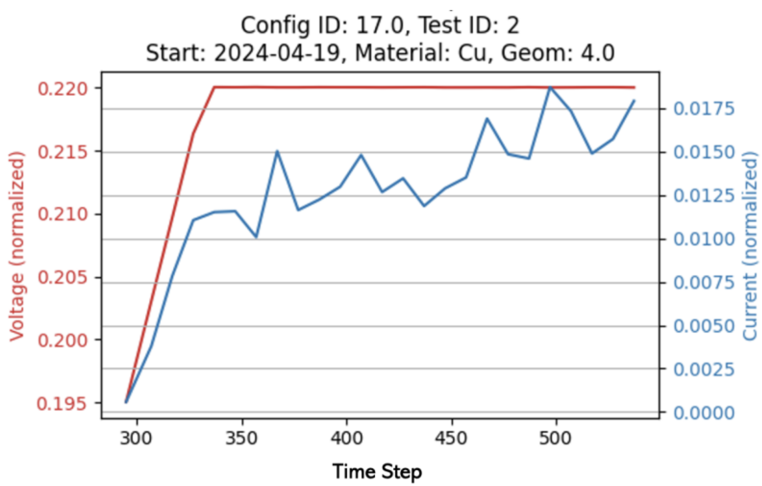
- Using Gradient Boosting

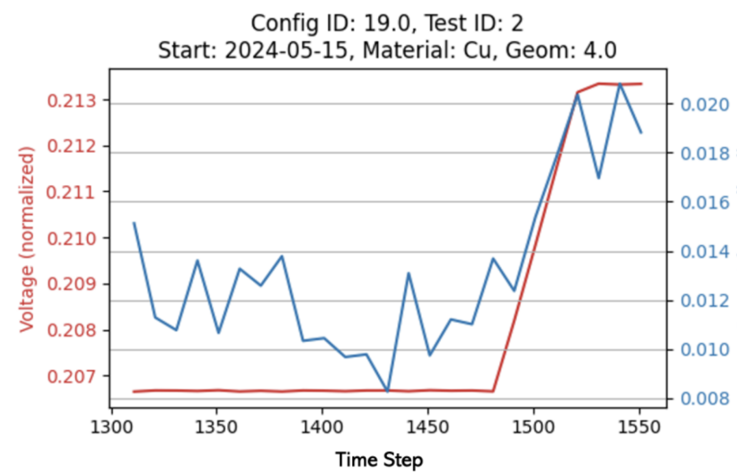
- Number of features: 34
- Number of targets: 10

Segment examples



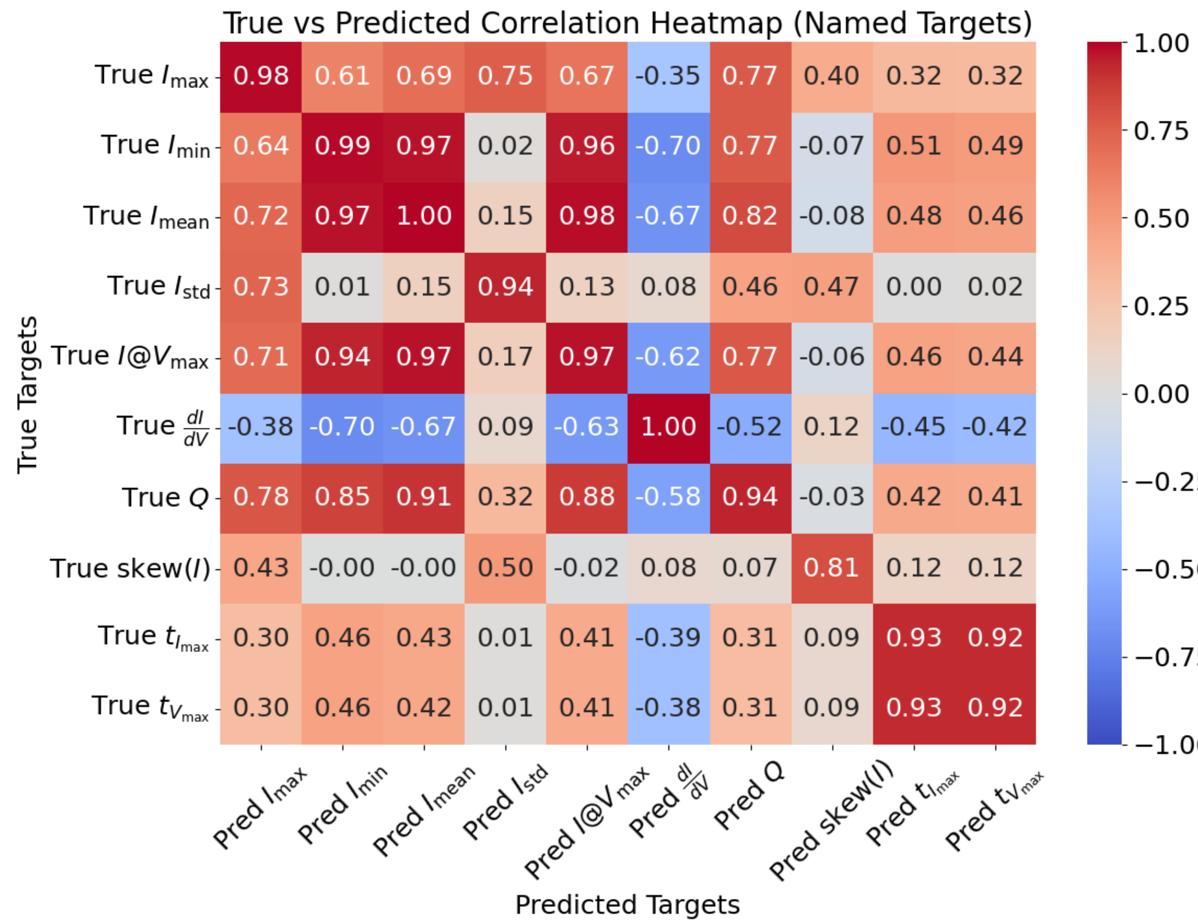






Performance of Trained Model

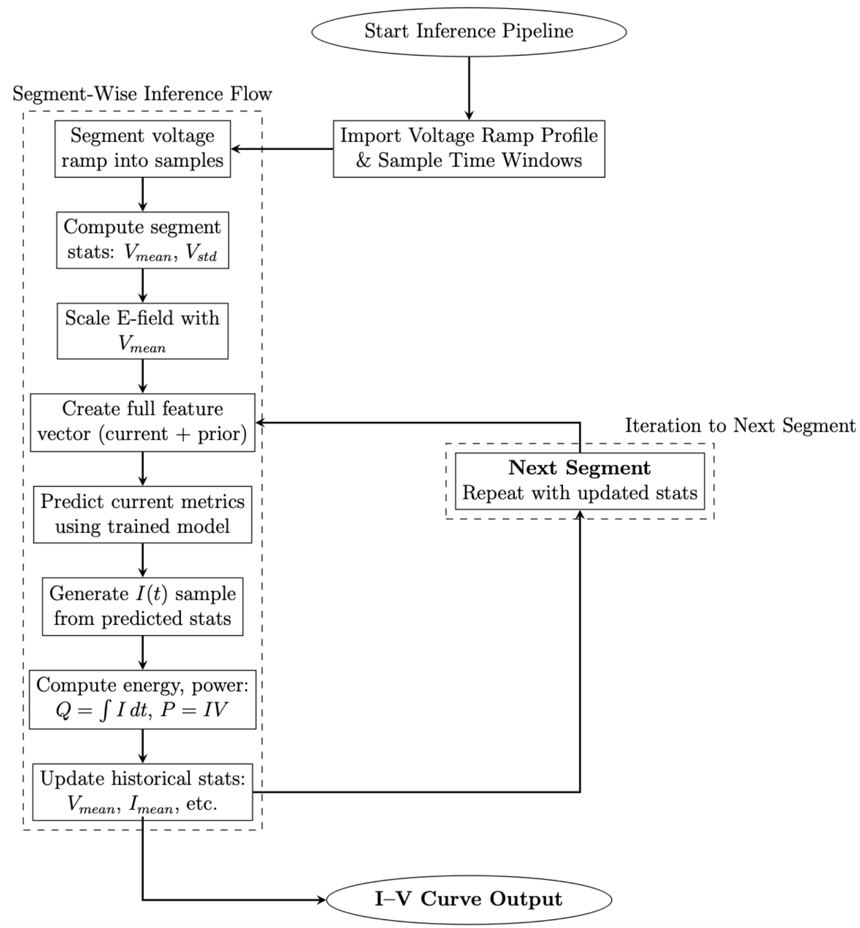
- R_2 score: 90.07%
- Number of estimators: 51
- Max Depth: 7
- Great at predicting aggregate and peak behaviors
- Stumbles on the more irregular, spike-related aspects of field emission.
- Not removing current spikes results in ~20% accuracy drop.



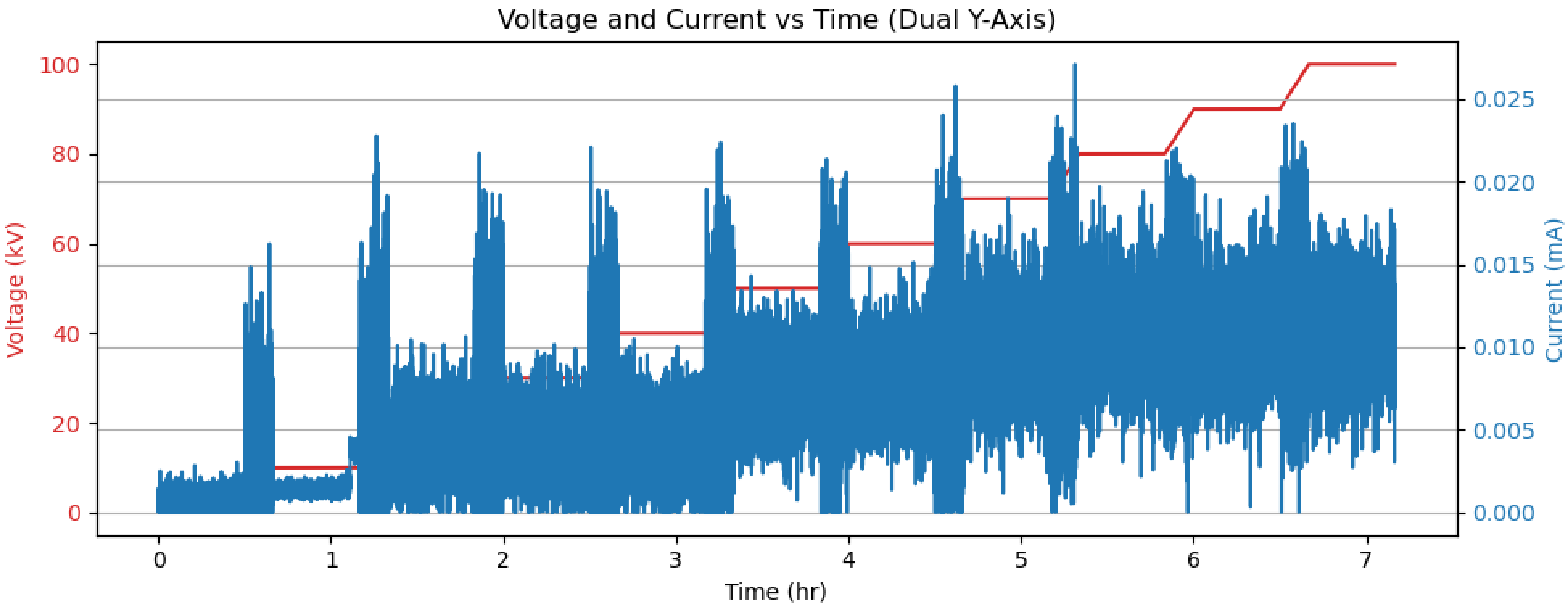
How to build a current profile?

Feature	*#*
Test ID	1
Subtest ID	1
Power Supply ID	1
Elapsed Time	1
Mass flow (pressure)	1
Energy	1
Peak Power	1
R_{series}	1
Cathode Area	1
Work Function	1
Surface Finish	1
E-Field Scaled to V_{curr}	6
V_{prior} and I_{prior} (max, μ, σ)	6
V_{prev} and I_{prev} (max, μ, σ)	6
V_{curr} (min, max, μ, σ)	4
	34

Target	*#*
I_{max}	1
I_{min}	1
I_{mean}	1
$I_{std\ dev}$	1
$I_{V_{max}}$	1
I_{skew}	1
$t_{V_{max}}$	1
$t_{I_{max}}$	1
dI/dV	1
$Q_{subtest}$	1
	10



An example of predicted current profile



Summary

- Field emission current is an important parameter for electron source, loss term, and input of the PIC simulations
- Few well-known ML models were benchmarked to predict stable field emission current → Achieved over 98% accuracy
- Conducted a feasibility analysis on capturing the temporal behavior by training gradient boosting on four configurations → achieved over 90% accuracy
- A simplistic approach relying on a nexus of available information to predict a hardly predictable phenomenon.
- We invite collaborations with available datasets or model generalization.

Thank you.

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