🚀 Gridded Ion Thruster — Physics → ML → Real-Time Dashboard

Physics-based simulation and machine learning surrogate model for a RF gridded ion thruster, enabling real-time performance prediction and inverse design optimization.

📌 Project Overview

This project implements a complete end-to-end pipeline for modeling and optimizing a Gridded Ion Thruster (GIT):

Physics simulation → dataset generation → neural surrogate model → interactive engineering dashboard

The goal is to replace expensive plasma simulations with a fast surrogate model capable of:

- real-time thrust prediction
- exploration of the thruster operating parameter space
- inverse optimization

The physics model is based on:

> Global model of a gridded-ion thruster powered by a radiofrequency inductive coil
> Chabert et al., Physics of Plasmas (2012)
> DOI: 10.1063/1.4737114

🧭 Pipeline Architecture

```
Phase 1 — Physics Solver (0D plasma model)
        ↓
Phase 2 — Synthetic dataset generation (5k simulations)
        ↓
Phase 3 — Neural surrogate model training
        ↓
Phase 4 — Real-time interactive dashboard
```

Each phase is modular and can be run independently.

⚛️ Phase 1 — 0D Global Model (Physics Solver)

Physics-based ground truth solver for the plasma inside the discharge chamber.

Overview

Implements a zero-dimensional global plasma model that solves coupled ODEs describing:

- plasma density
- neutral density
- electron temperature
- gas temperature

The solver integrates until steady-state and is used as:

- ground truth generator
- validation baseline
- dataset generator for ML model

State Variables

- `n` — plasma density (m^{-3})
- `ng` — neutral gas density (m^{-3})
- `Te` — electron temperature (eV)
- `Tg` — neutral gas temperature (K)

Simulation Routines

Power Sweep

RF Power: 100 → 1600 W
Used to validate behavior against literature.

Mass Flow Optimization

Mass flow: 0.5 → 40 mg/s
Finds saturation where:

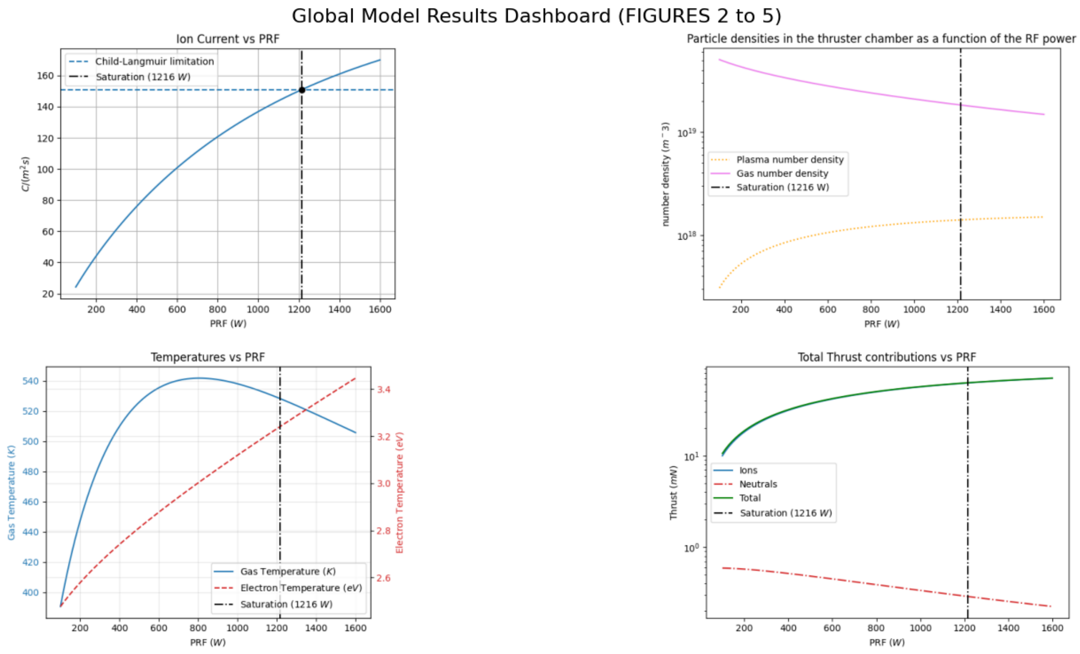
```
Ion current density → Child-Langmuir limit
```

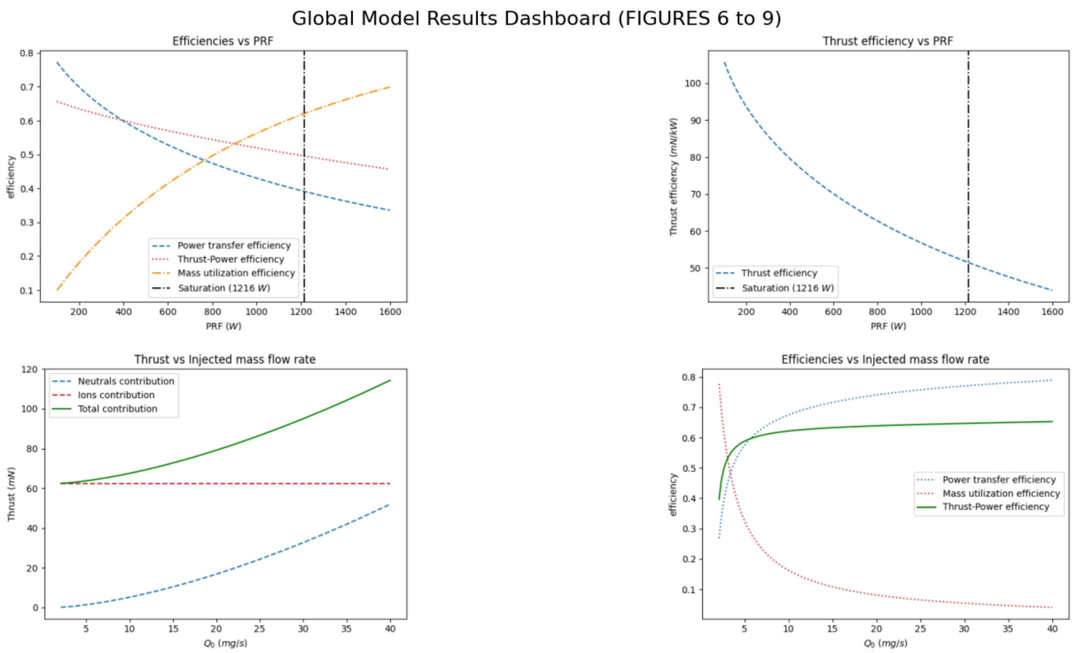
Outputs

Two analysis dashboards with key figures:

- ion current density vs power
- densities vs power
- temperatures vs power
- thrust components
- efficiency metrics
- thrust vs mass flow

Generated figures





Run

```
python physics_solver.py
```

Dependencies

```
numpy
scipy
matplotlib
```

📊 Phase 2 — Synthetic Dataset Generation

Transforms physics simulations into a dataset for ML training.

Goal

Generate 5,000 operating points across the thruster envelope.

Why:

- physics solver = slow (seconds per run)
- ML requires large dataset
- enables real-time prediction later

Techniques

Latin Hypercube Sampling

Ensures uniform coverage of parameter space.

Ranges:

- RF Power: 50 → 2500 W
- Mass flow: 0.5 → 40 mg/s

Parallel Computing

Uses Python multiprocessing:

- splits workload across CPU cores
- near-linear speedup
- reduces runtime from hours to minutes

Output Dataset

```
GlobalModel_Dataset.csv
(in the folder there is also dataset.png, a plot tho rapresent the data generated during the Phase 2)
```

Columns:

Input_Power_W	Input_Flow_mg_s	Output_Thrust_mN	Success

Run

```
python data_processing.py
```

Dependencies

```
pip install pandas scipy
```

🧠 Phase 3 — ML Surrogate Model

Neural network approximating the plasma physics model.

Goal

Replace ODE solver with fast inference model.

Result:

```
seconds → milliseconds
```

Data Pipeline

- Remove failed simulations
- Train/test split (80/20)
- Min-max normalization
- Save scalers for deployment

Neural Architecture

Layer	Neurons	Activation
Input	2	—
Dense	64	ReLU
Dense	64	ReLU
Output	1	Linear

Loss: MSE
Optimizer: Adam
Epochs: 100
Batch: 32

Generated Artifacts

```
git_surrogate_model.keras
scaler_X.pkl
scaler_y.pkl
```

Run

```
python train_model.py
```

Dependencies

```
pip install tensorflow scikit-learn joblib pandas matplotlib
```

🖥 Phase 4 — Interactive Dashboard

Real-time engineering interface for simulation and optimization.

Features

Real-Time Prediction

Interactive sliders:

- RF Power
- Mass Flow

Pipeline:

```
input → normalization → NN inference → denormalization → thrust
```

Latency: < 50 ms

Inverse Design Optimization

Target thrust → find optimal configuration.

Monte Carlo search:

- 50k random configurations
- filter by target thrust
- return optimal solutions

Outputs:

- minimum power configuration
- minimum propellant configuration

Robustness

- cached model loading
- error handling
- fast UI response

Run Dashboard

```
streamlit run app.py
```

Dependencies

```
pip install streamlit tensorflow pandas numpy joblib
```

🧩 Project Structure

```
physics_solver.py
data_processing.py
train_model.py
app.py

git_surrogate_model.keras
scaler_X.pkl
scaler_y.pkl
GlobalModel_Dataset.csv
```

🎯 What This Project Demonstrates

- physics-based plasma modeling
- scientific computing (ODEs)
- dataset engineering
- surrogate modeling
- neural regression
- real-time engineering tools
- inverse design optimization

🔮 Possible Extensions

- 2D/3D plasma model coupling
- Bayesian optimization
- uncertainty quantification
- reinforcement learning control
- deployment as web service