Recurrent neural network-based digital twin of ST40 tokamak dynamics: building system insight into model architecture

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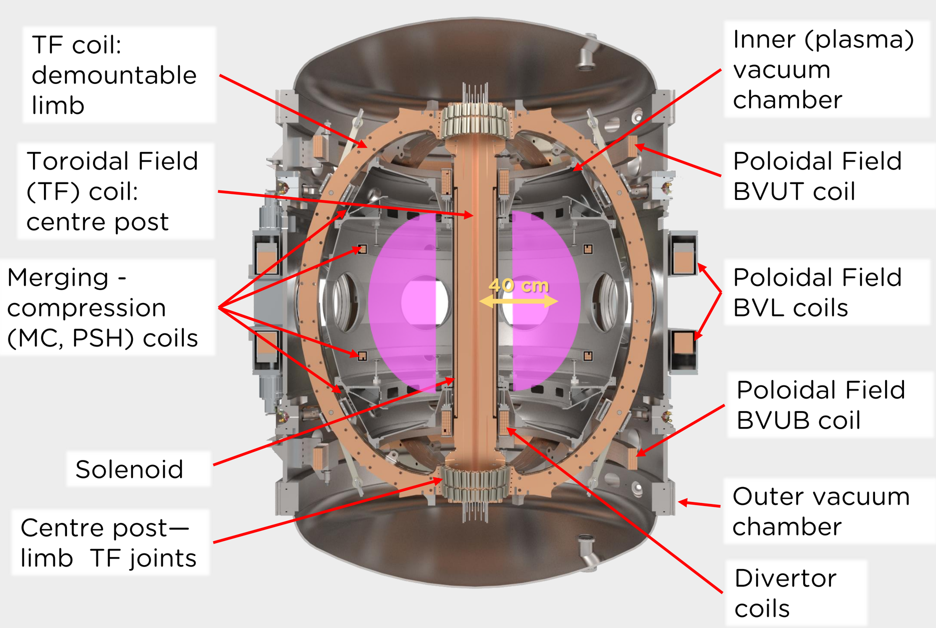
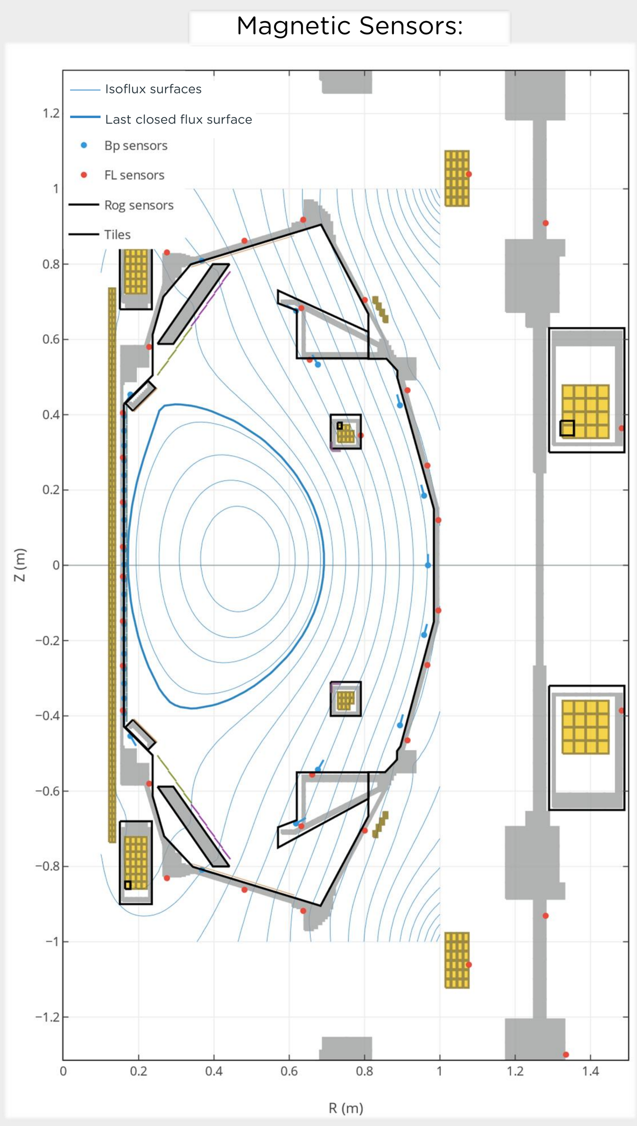
A digital twin for plasma dynamics in a tokamak is useful for optimising and validating experimental scenario proposals, developing plasma control systems and more. Physics-based modelling of the entire tokamak discharge process is challenging due to nonlinear, multi-scale, multi-physics characteristics of the tokamak and demands time from a diverse team of experts as well as computational resources to achieve high-fidelity simulations. Furthermore, simulation-time of physics-based models is prohibitively long for some application types. These challenges invite the use of machine learning (ML) as a complimentary tool for developing a fast and accurate digital twin.

Poster Summary:

- **A hybrid ML/physics-based digital twin for plasma dynamics in ST40 spherical tokamak [1].**
- **Long-Short Term Memory (LSTM) [2] recurrent neural networks are used for time-series predictions.**
- **ST40 specifics that guided the choice of the digital twin architecture are discussed.**
- **It is shown that the digital twin can automatically recognise and reproduce:**
  - **plasmaless ST40 operation,**
  - **merging-compression plasma startup [3-5],**
  - **plasma flattop dynamics and transition to vertical displacement event,**
  - **some types of disruptions.**

The ST40 high-field spherical tokamak

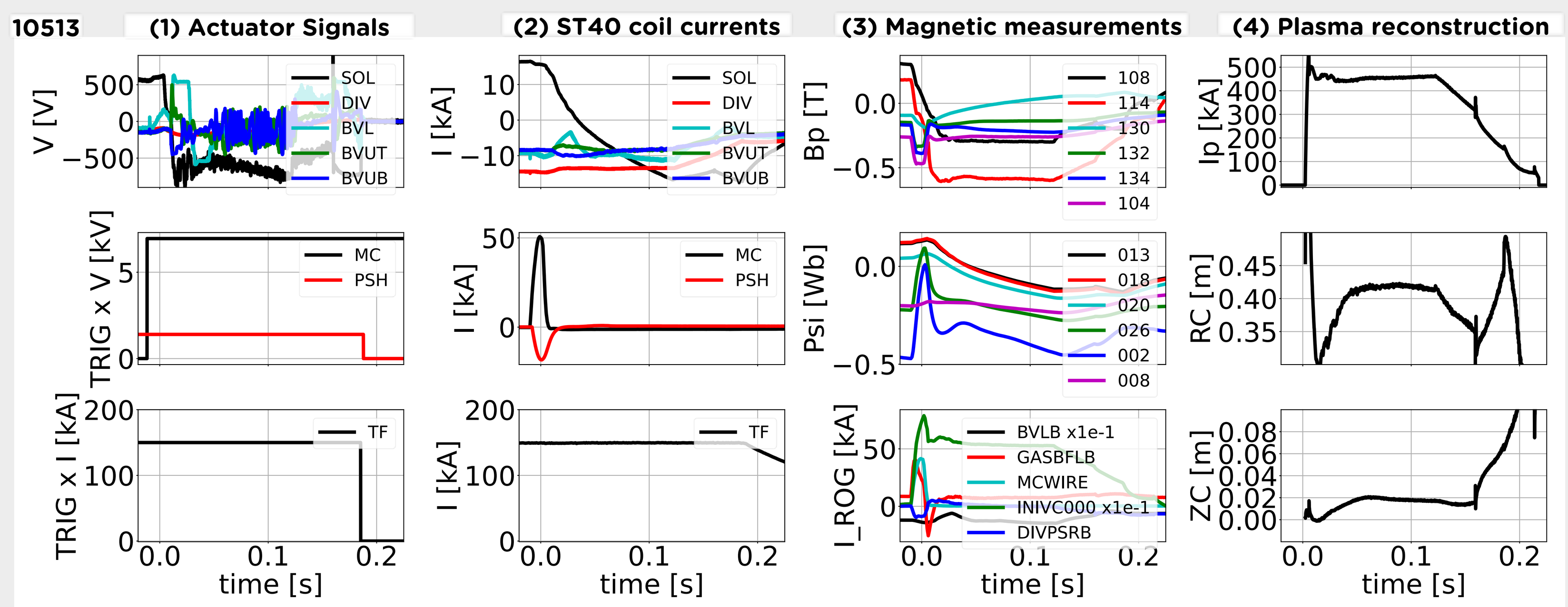




Parameter	Range
B_t [T]	1.5 – 2.2
I_p [MA]	0.4 – 0.8
R_{Geo} [cm]	40 – 50
A = R/a	1.6 – 1.8
P_{NB}, E_{NB} [MW, keV]	0.8, 24; 1.0, 55
Pulse duration [ms]	~200

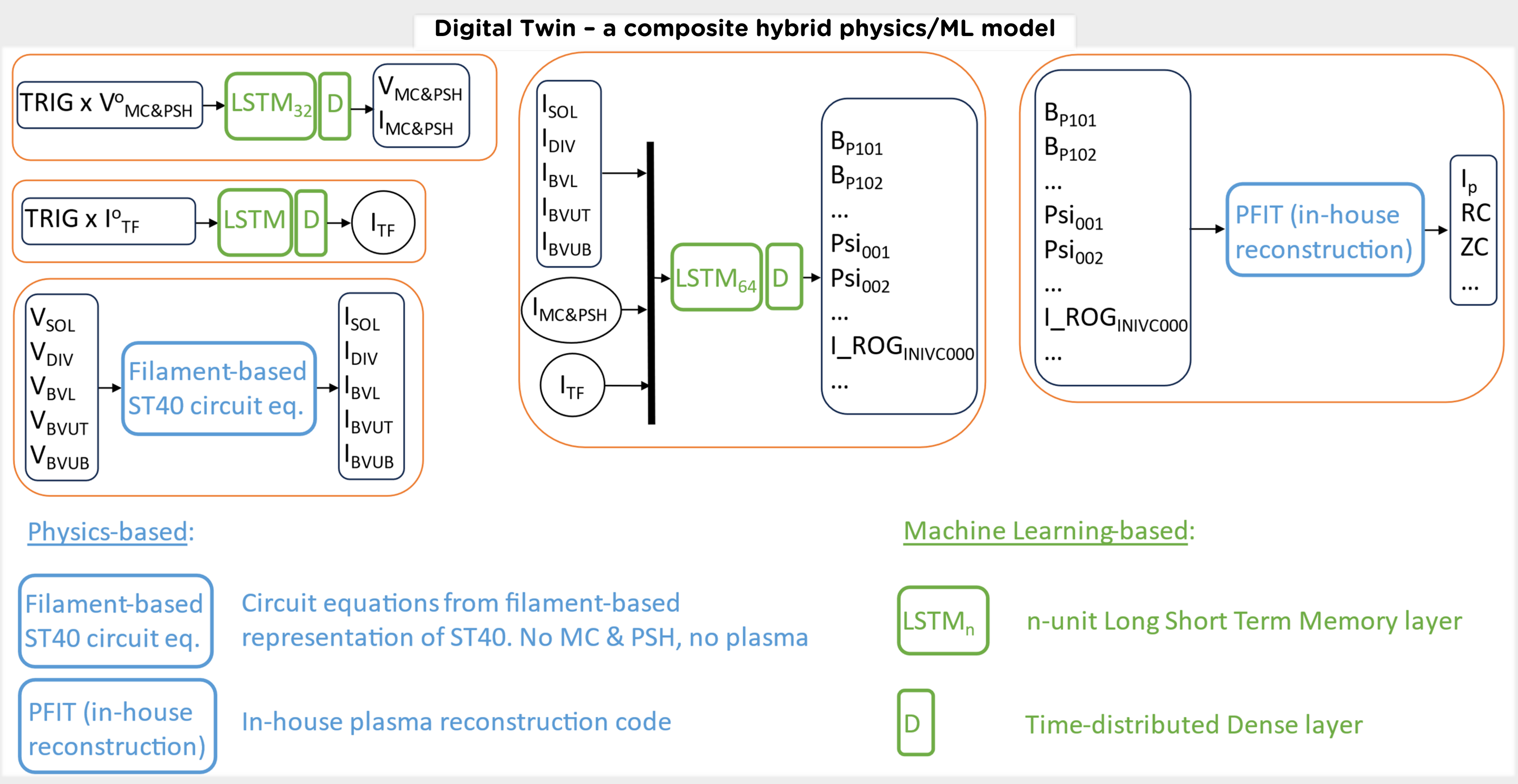
Typical plasma pulse dynamics

- Slow ramp up of Poloidal Field (PF) coil currents
- Plasma startup due to Merging Compression (MC & PSH) coil current ramps
- Plasma flattop dynamics
- Controlled plasma current ramp down
- Often there are partial/full disruptions: Loss of control, plasma touching walls, impurity influx



Digital Twin model structure

- Inputs – Plasma Control System (PCS) actuator and control signals:
  - Poloidal Field (PF) coil voltage requests
  - Merging Compression (MC) circuit PSU pre-charge voltages and digital trigger signals
  - Toroidal Field (TF) coil target current and power supply digital trigger signal
- Outputs – magnetic sensor signals: flux loops, poloidal-plane B-field (Bp) probes, Rogowski coils
- Digital Twin is comprised of a collection of smaller physics- and ML-based models:



Digital Twin training procedure

- Data: 2023 Feb – Sep. campaign plasma pulses subset without neutral beams (185 pulses)
- Data are split in 70% : 20% : 10% ratio for train : validate : test subsets (130 : 37 : 18 pulses)
- Simplifying assumptions:
  - coil currents and magnetic measurements fully characterise plasma dynamics
  - other conditions affecting plasma dynamics are assumed "constant" and excluded from training data, e.g. gas valve waveforms and plasma density, wall conditioning info
- The Neural Network (NN) at the core of Digital Twin outputs raw magnetic sensor signals
- Reconstructed plasma info, e.g. current, centroid position, last closed flux surface – are **not** part of model outputs or learning cost function.
- All presented NN results are for test set pulses (pulses unseen during model training)

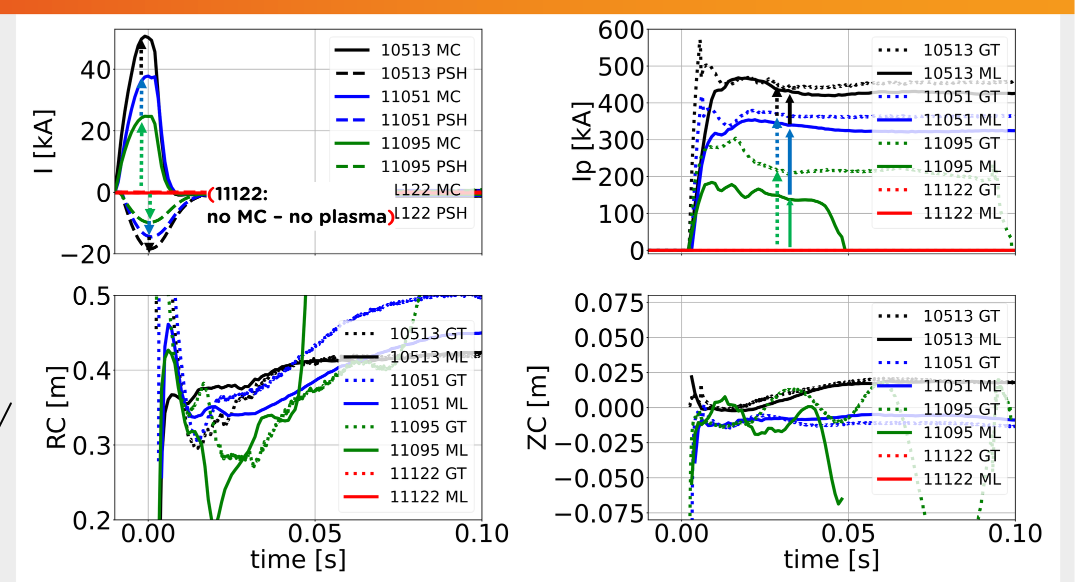
NN merging-compression startup

Top-left: experimental MC & PSH currents (at ITF = 150kA)

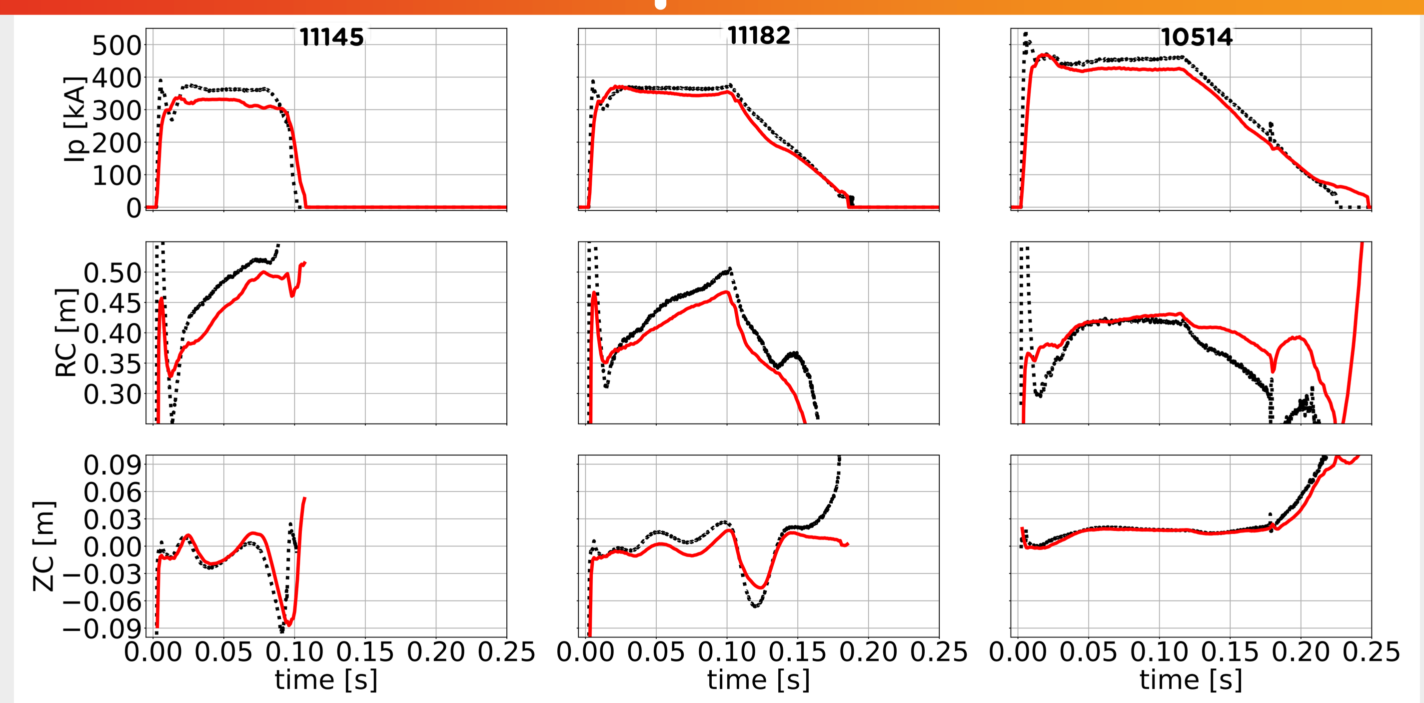
Top-right: plasma current

Bottom left to right: plasma radial and vertical centroid position

Dotted/solid lines: reconstruction from experiment (ground truth 'GT')/ prediction (ML)

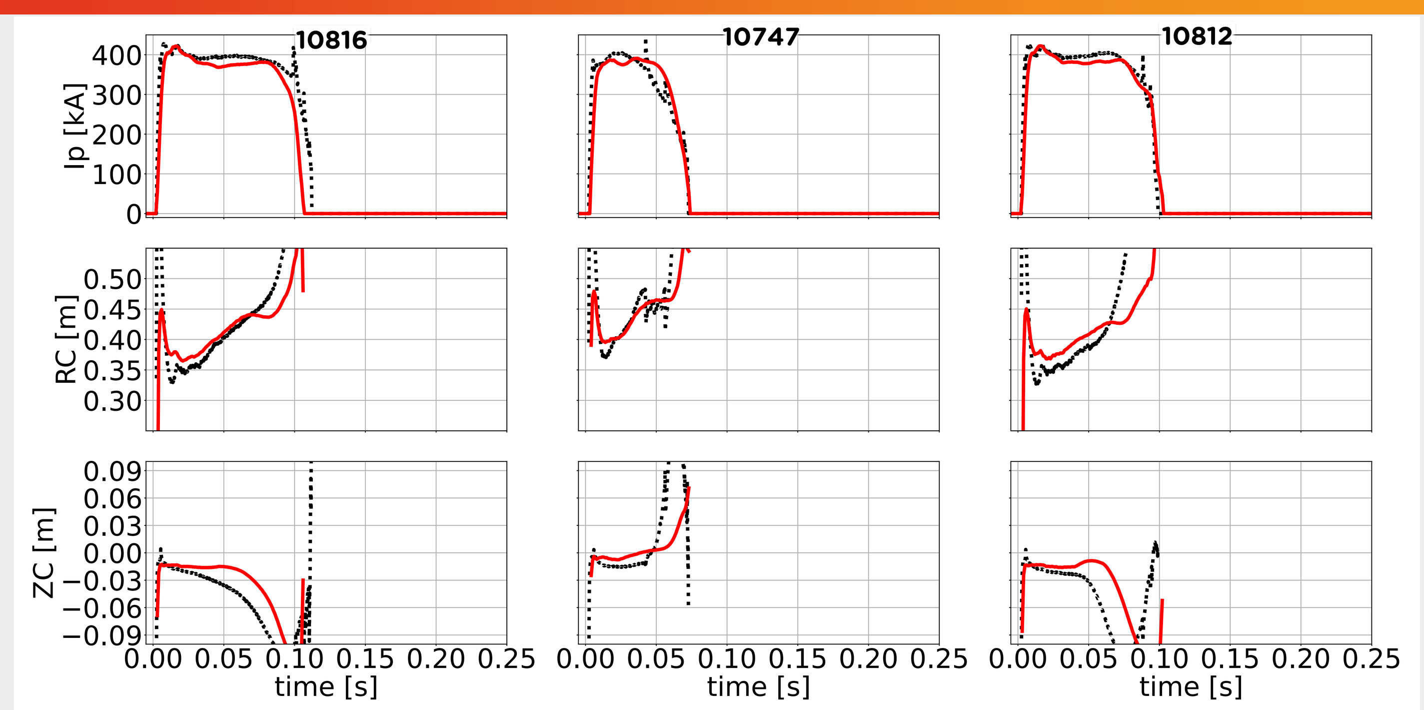


NN plasma flattop dynamics and transition to vertical displacement event



Experiments 11145, 11182, 10514. Top to bottom: Plasma current, radial and vertical centroid positions. Dotted black/solid red lines: reconstruction from experiment/prediction.

NN exhibits some disruptions



Experiments 10816, 10747, 10812. Top to bottom: Plasma current, radial and vertical centroid positions. Dotted/solid lines: reconstruction from experiment/prediction.

Conclusions and Future work

Proof-of-principle Digital Twin has been demonstrated. Three main avenues of further work:

1. Include more physics in the Digital Twin
2. Improve accuracy of predictions
3. Deploy applications based on the Digital Twin

1. Including more physics:
   - Extend inputs/outputs with neutral beam and H-alpha emission. Hence:
   - Simulate dynamics of L-H and H-L transitions
   - Simulate actuation effect on plasma current, radial position and other properties
2. Improving accuracy – address corrupted NN training data due to sensors' damage:
   - A subset of sensors got perturbed and damaged during campaign, modifying their response
   - Hence NN training data is corrupted
   - Devise strategy to deal with corrupted training data and retrain the model
3. Applications:
   - Experimental inputs validation
   - Plasma Control System test platform
   - Inter-pulse fast scenario optimisation

References

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