The Lehigh Advantage: A Unique Synergy of Physics, Control, and AI/ML

From Gyrokinetic Simulations and Anomalous Transport Modeling to Disruption-free, Machine-safe, High-performance Reactor Operation via Physics-informed and AI-empowered Advanced Controls

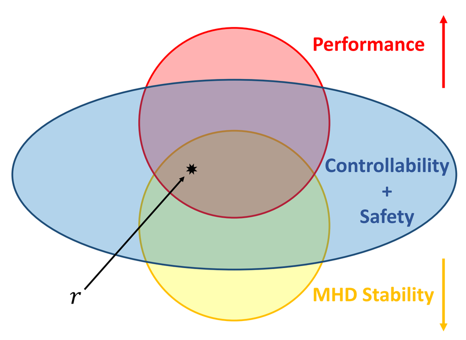
LEHIGH UNIVERSITY PLASMA CONTROL GROUP
Prof. Eugenio Schuster (Director), Prof. Tariq Rafiq (Co-Director)

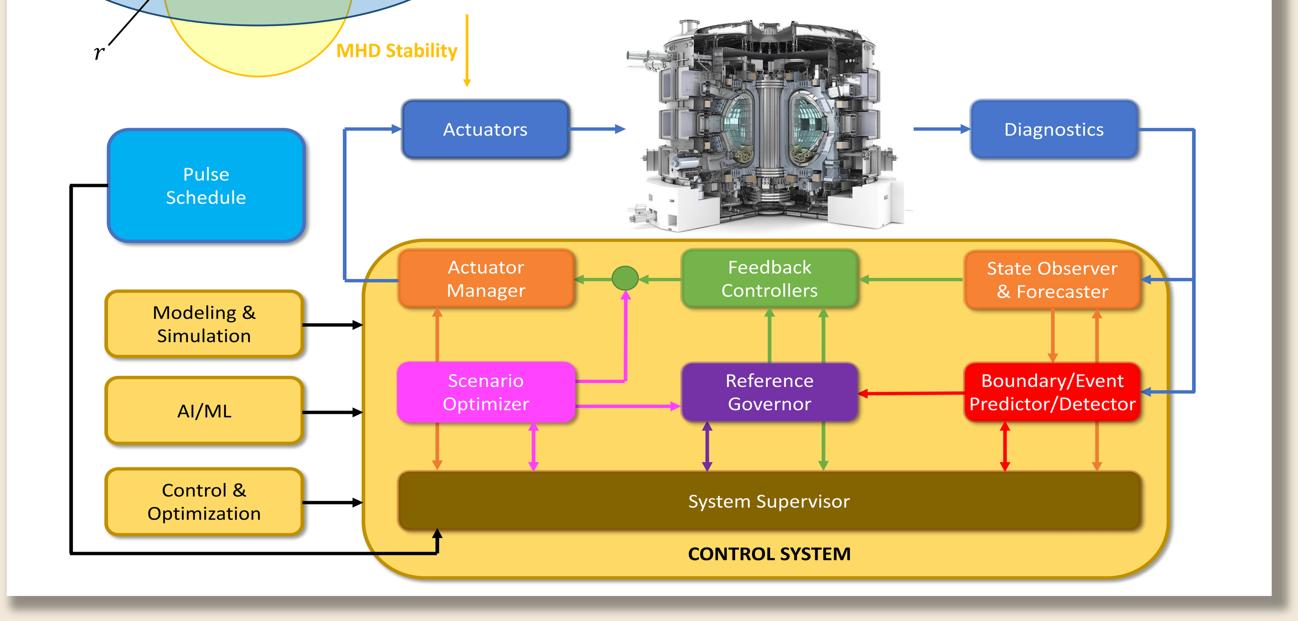
Work supported by U.S. Department of Energy, Office of Science, Office of Fusion Energy Sciences (DE-SC0010661, DE-SC0010537, DE-SC0021385, DE-SC0013977)

Disruption-Free, Machine-Safe, High-Performance Reactor Control

Bridging fundamental physics modeling with AI-empowered, model-based controls for reactor-ready operation

- Predict, Sustain, and Control Burning Plasmas
  - ❑ Model + Data (AI/ML) → Reactor-grade Control
- Goal: Design of Controller + Observer + Actuator Manager but also real-time setting of *operating point or scenario r*
  - ❑ Tradeoff between performance and MHD stability within controllability and safety boundaries through Reference Governor + Boundary/Event Predictor
- Observer + Actuator Manager decouple Controller from Actuators + Diagnostics → Robust Fault-tolerant Control



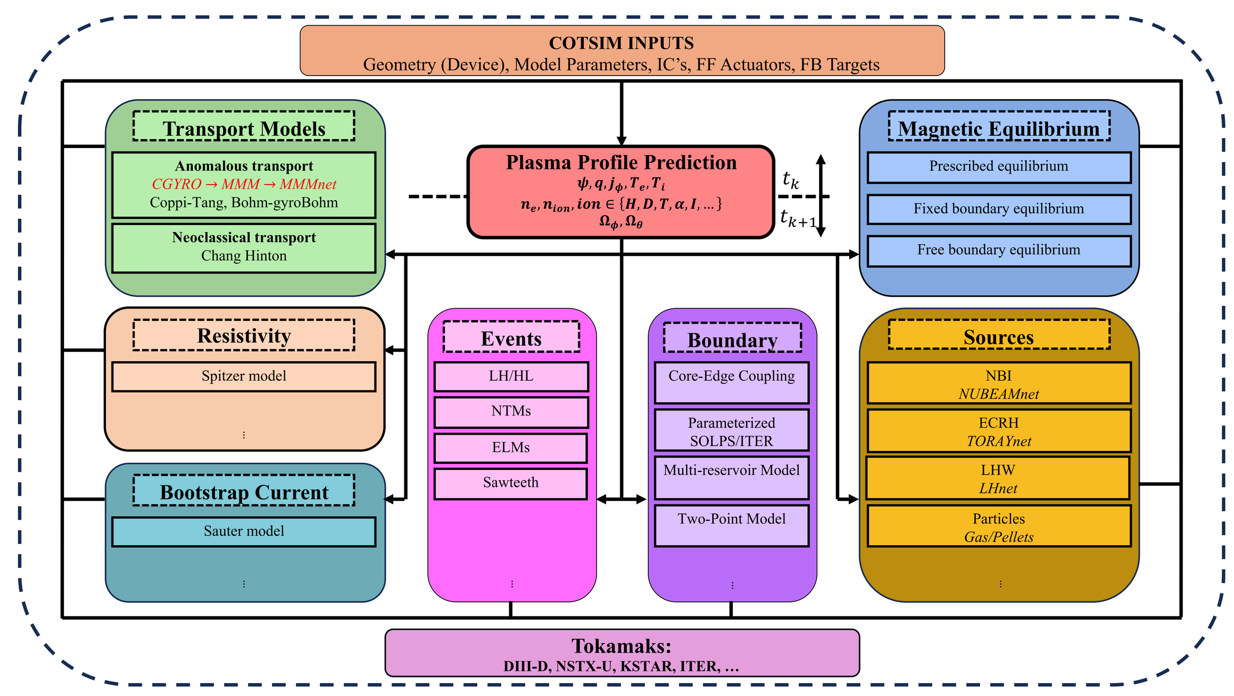


Reactor Digital Twin Powered by Fast, Accurate, NN-based COTSIM

- 1D → 1.5D transport code
- 2D MHD Equilibrium
  - Prescribed
  - Analytical (Fixed Bdry)
  - Numerical (Free/Fixed Bdry)
- Hybrid Finite Differences
  - Variable space/time steps

- Transport Engine: MMM
- Fast (full shot → sec/min)
  - Enables iterative design
- After model reduction
  - Real-time
  - Faster-than-real-time
- Core + Edge + Events

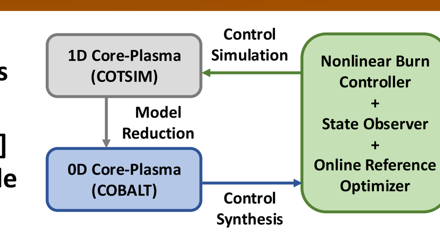
- Modular configuration
  - Custom physics complexity
  - Accuracy vs. Speed tradeoff
- Matlab/Simulink-based
  - Control-design friendly
  - Closed-loop capable
  - Optimizer wrappable

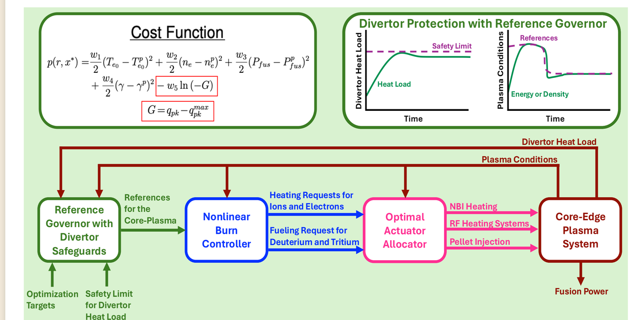


Divertor-safe Nonlinear Burn Control by Core-Edge Integration

Core-plasma kinetic (Burn) control → Critical to ITER/FPP

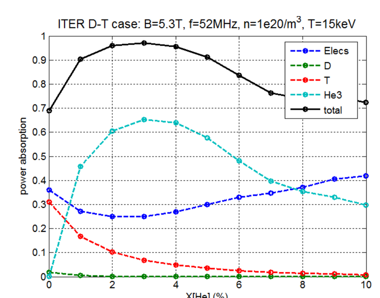
- Highly nonlinear dynamics and coupling with other controllers
- Control objective is zero-dimensional (0D): $P_f, Q, G, \gamma, \cdots$
- Approach: 0D nonlinear controller tested in 1D simulations [1]
- 0D Control-Oriented Burning plAsma simuLaTor (COBALT) code
  - ✦ Multi-temp (ion, electron), multi-species (D, T, α, impurity)





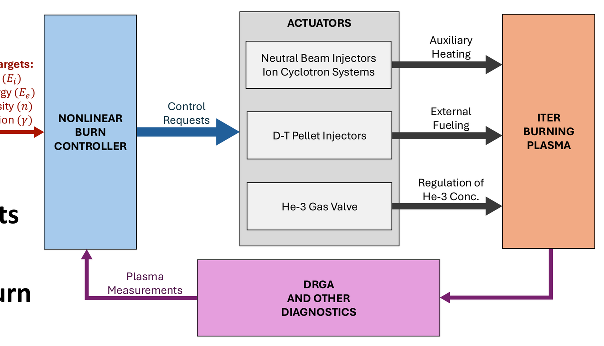
Core-edge integrated models are key enablers:

- Assess divertor limits on ITER operational space
  - ✦ Plasma OPerational CONtour (POPCON) plots
- Design reference governors for safe operation [2]
  - ✦ Online optimizer → Reference to controller
  - ✦ Regimes of high fusion power + divertor safety



ICRF Power Optimization:

- He-3 gas puffing
- DRGA measurements
- Simultaneous ICRH power tailoring + burn control [3], [4]

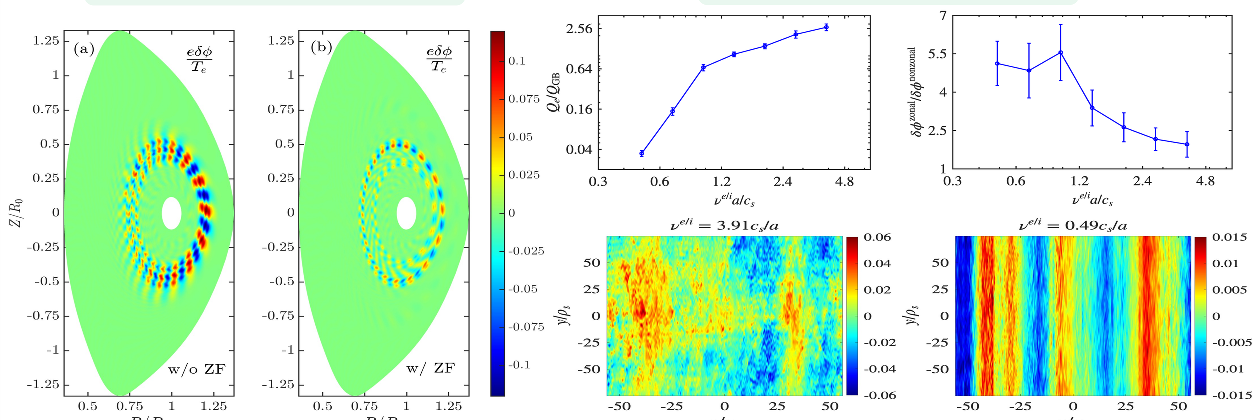


[1] V. Graber, E. Schuster, "One-dimensional Simulations of Nonlinear Burn Control in ITER," Fusion Engineering and Design 221 (2025) 115362.
[2] V. Graber and E. Schuster, "Divertor-safe nonlinear burn control based on a SOLPS parameterized core-edge model for ITER," Nuclear Fusion (2024).
[3] C. Klepper et al. "Feasibility of fusion plasma burn control via real-time, sub-divertor neutral gas isotopic and compositional analysis," Nuclear Fusion 65 (2025).
[4] V. Graber et al., "Burn Control in ITER by Maximization of Ion Cyclotron Power Absorption Through Regulation of Helium-3 Concentration," IAEA-FEC 2025 → PPCF.

Gyrokinetic Simulations: Role of Instabilities in Turbulent Transport

- Transport in NSTXU driven by plasma turbulence from KBMs and MTMs instabilities limits plasma performance by constraining achievable pressure profiles and enhancing electron thermal transport.
- Nonlinear gyrokinetic simulations reveal the critical role of zonal flow in regulating the turbulent and transport associated with Kinetic Ballooning Modes (KBMs) and Micro Tearing Modes (MTMs).

KBM regulation by zonal flow | MTM regulation by zonal flow

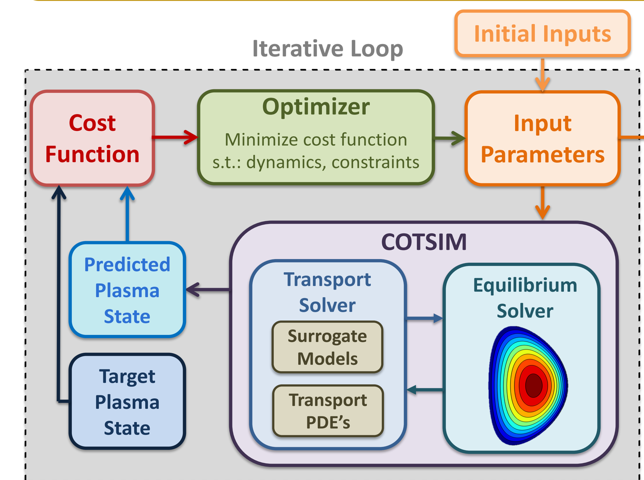


- Zonal flows reduce the amplitude of KBM-driven fluctuations by breaking large eddies into smaller structures and shortening the radial correlation length [1].
- Scaling of electron thermal transport with electron-ion collisionality reveals a transition to a low collisionality regime, where enhanced zonal flow and zonal fields play a key role in suppressing MTM turbulence [2].
- Zonal flows act as a self-generated regulator of turbulence, mitigating KBM and MTM transport and improving confinement in NSTX-U-like plasmas.

[1] T. Singh et al., "Global Gyrokinetic Simulations of Kinetic Ballooning Mode in NSTX-U Plasmas," Nuclear Fusion 65, 106039 (2025).
[2] T. Singh et al., "Nonlinear Gyrokinetic Simulations of Microtearing Modes in NSTX and NSTX-U-like Plasma," to be submitted (2025).

Model-based Equilibrium + Transport Optimal Scenario Planning

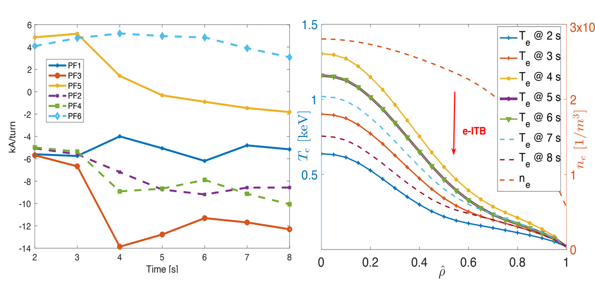
- Goal: Use COTSIM to optimize plasma equilibrium/transport during tokamak discharge
- The Cost Function J mathematically represents the desired (user-defined) control objectives

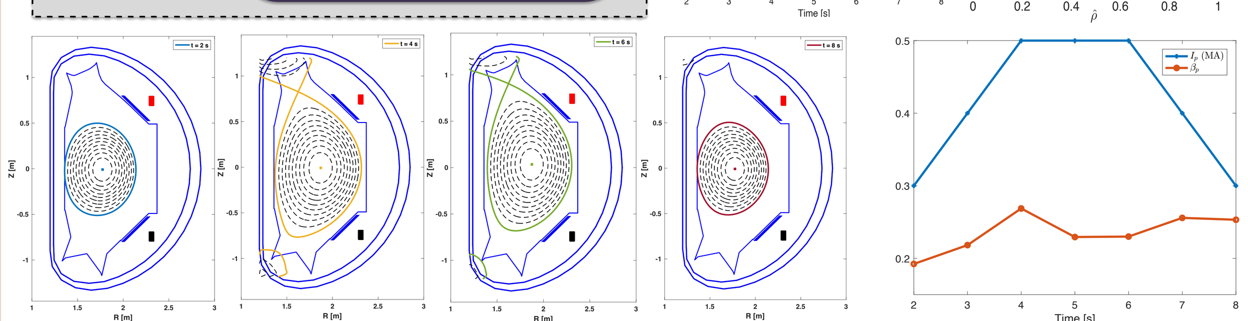


Problem Statement: $\min_u J(y, u, y^{target})$ s.t.

$\dot{x} = f(x,u), y = g(x), c(x,u) < 0$

- $f(x,u), g(x)$: State Dynamics
- $c(x,u)$: Input/State Constraints



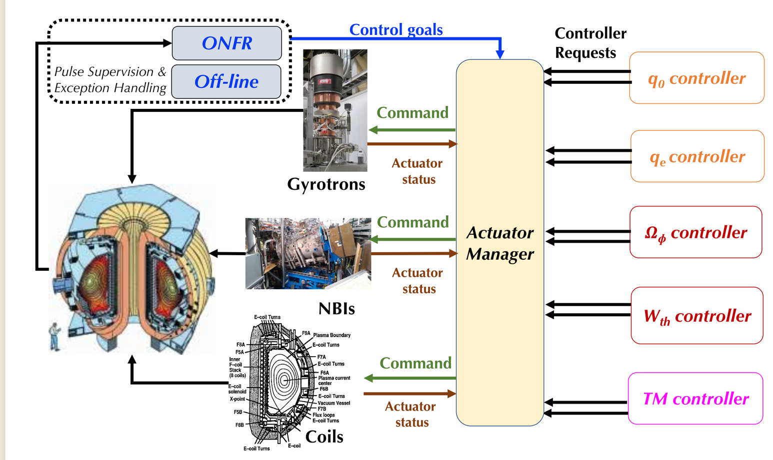


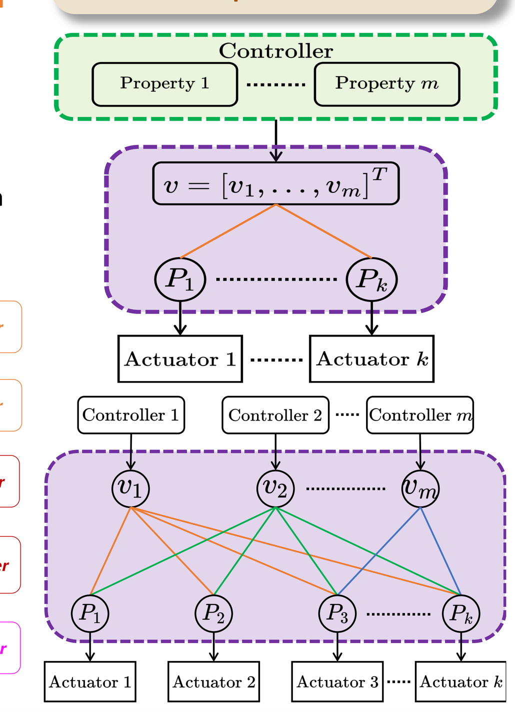
[1] X. Song et al., "Model-based Scenario Optimization in Tokamaks by Integrating Free-boundary Equilibrium and Fast Transport Solvers," EPS-CPP, Bordeaux, France, 2023.
[2] S. Morosohk et al., "Machine Learning-Enhanced Model-Based Scenario Optimization for DIII-D," Nuclear Fusion 64 (2024) 056018 (11pp).

Control Integration by Nonlinear Actuator Sharing Algorithms (ASAs)

- Reactor-grade PCS must control multiple properties
  - Controllers generate individual input commands $v_1, v_2 \dots,$
  - Actuators require physical actuator requests $P_1, P_2, \dots$
  - ASAs convert v_i to P_j $(i, j \in \mathbb{Z}^+)$ by real-time optimization
- Static ASAs [2]: $v_i - P_j$ relation → algebraic equations
  - Based on solving a quadratic programming problem
- Dynamic ASAs [3,4]: $v_i - P_j$ relation → differential equations
  - Based on solving a minimax optimization problem
  - Online reinforcement learning can solve allocation problem
- Optimization-based ASA tested in DIII-D (leveraging ONFR)

When multiple control objectives are not integrated in single algorithm [1], actuator sharing strategies must arbitrate competition for actuators





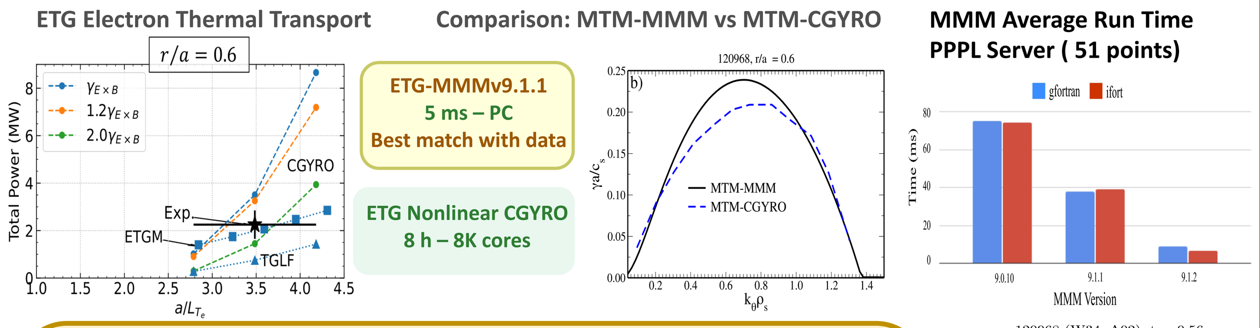
[1] S. Morosohk et al., "Simultaneous control of electron temperature and safety factor profiles in DIII-D using model-based optimal control techniques," PPCF (2025).
[2] S. T. Paruchuri et al., "Static actuator-sharing algorithm for concurrent control of multiple plasma properties," PPCF 67.1 (2024): 015005.
[3] S. T. Paruchuri et al., "Dynamic Actuator Allocation via Reinforcement Learning for Concurrent Plasma Control Objectives," IEEE TPS 52.9 (2024): 4140-4146.
[4] A. Pajares et al., "Integrated control of individual plasma scalars with simultaneous neoclassical tearing-mode suppression," Nuclear Fusion 62 (2022) 036018 (22pp).

Physics Based Anomalous Transport Modeling by MMM

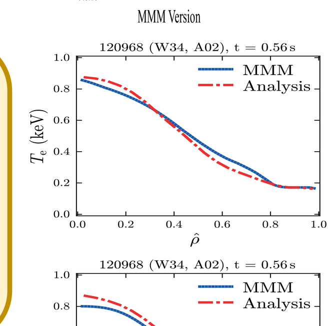
Multi-Mode Model (MMM): Integrates drift-wave and MHD-like modes for predictive tokamak simulations, predicting electron & ion temperature, electron & impurity density, and toroidal & poloidal rotation profiles

Instabilities / Modes	Verification	Validation
ITG / ETG / TEM / MTM / DRIBM / KBM / Peeling / High-n MHD modes	Verified against gyrokinetic codes Predictions grounded in fundamental physics [1,2]	Validated across multiple tokamaks RMS deviation within experimental uncertainty [3,4]

ETG Electron Thermal Transport | Comparison: MTM-MMM vs MTM-CGYRO | MMM Average Run Time PPPL Server (51 points)

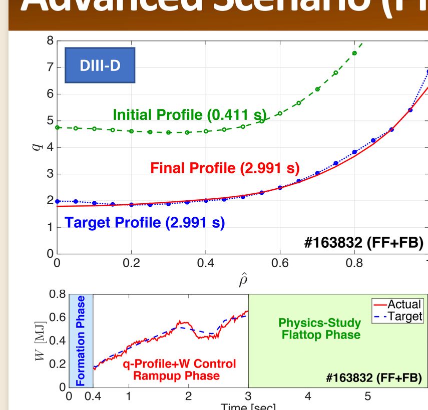


- MMMv9.1.2 is more suitable for time-critical applications:
  - ❑ Control-oriented modeling
  - ❑ Uncertainty quantification
  - ❑ Scenario optimization in tokamak plasmas
- >15× faster between v9.0.10 → v9.1.2 (ifort vs gfortran)
- 5ms to calculate electron/ion-scale modes and 6 diffusivities (51 radial pts)
- Consistent reproduction of profile shapes across NSTX, DIII-D, EAST, KSTAR
- Suitable for integrated frameworks (e.g., COTSIM, TRANSP, IMAS, OMFIT)



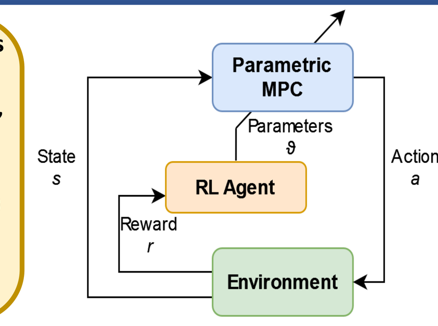
[1] T. Rafiq et al., ETG Driven Transport Model for Tokamak Plasmas, Physics of Plasmas 29, 092503 (2022).
[2] T. Rafiq et al., MTM and Electron Transport in Low/High Collisionality NSTX Discharges, Physics of Plasmas 28, 022504 (2021).
[3] T. Rafiq et al., Predictive Modeling of NSTX Discharges with the Updated MMM, Nuclear Fusion 64, 076024 (2024) .
[4] T. Rafiq et al., Validating the MMM's Ability to Reproduce Diverse Tokamak Scenarios, Plasma 6, 435 (2023).

Advanced Scenario (Profile) Control: MPC + RL + Moving Actuators



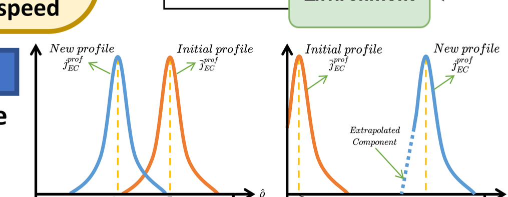
Profile Control by Real-time Optimization (MPC) + Learning (RL)

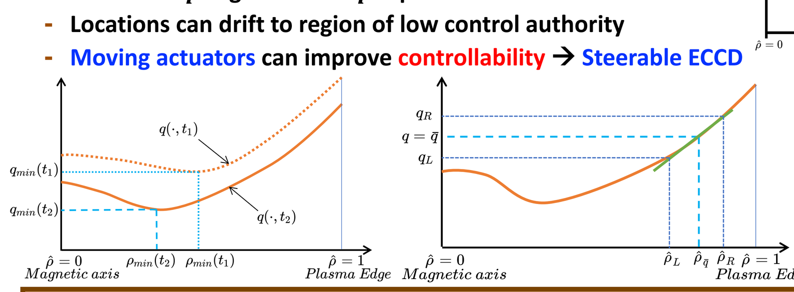
- FF optimal actuator trajectory is re-optimized in real time (FB)
- Conventional, Self-triggered [1], hybrid [2] MPC schemes with fixed and moving actuators [3]
- Model Predictive Control (MPC) has been augmented [4, 5] by Reinforcement Learning (RL) to increase performance + speed



Local Current-Profile Control by Spatially Moving Actuators

- Location of local q-profile properties can change over time
  - Minimum q or gradient of q at prescribed rational surface
  - Locations can drift to region of low control authority
  - Moving actuators can improve controllability → Steerable ECCD

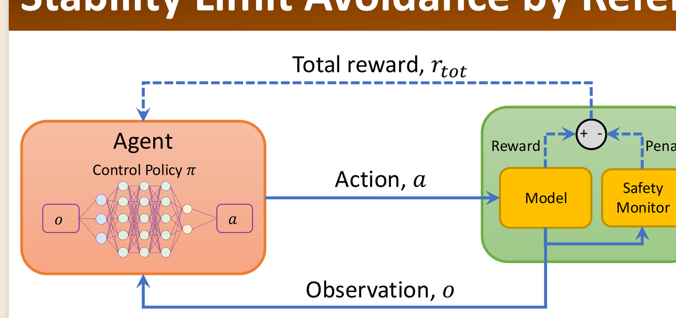




- Moving actuator can increase size of reachable (feasible) space
- Control of minimum q can deter or delay onset of instability [1]
- Control of local q gradient or slope around evolving q rational surface can also avoid instability [2]

[1] Z. Wang et al., "Safety Factor Profile Regulation via Self-triggered Model Predictive Control in the EAST Tokamak," ACC, Toronto, Canada, 2024.
[2] B. Leard et al., "Hybrid MPC for safety factor profile and stored energy regulation while incorporating NBI constraints," Nuclear Fusion 64 (2024) 086052 (15pp).
[3] S.T. Paruchuri et al., "Model Predictive Current Profile Control in Tokamaks by Exploiting Spatially Moving ECCD," Fusion Engineering & Design 192 (2023) 113796.
[4] Z. Wang et al., "Pellet Injection-based Model Predictive Control of the Density Profile in Tokamaks by Leveraging Deep Reinforcement Learning," IEEE SOFE, 2025.
[5] Z. Wang et al., "Safety Factor Profile Control in EAST via Reinforcement-Learning-based Model Predictive Control," IEEE CCTA, San Diego, CA, USA, 2025.
[6] S.T. Paruchuri et al., "Nonlinear control of the minimum q in tokamaks by optimal allocation of spatially moving ECCD," Fusion Engineering & Design 207 (2024) 114612 .
[7] S.T. Paruchuri, "Nonlinear Control of Safety Factor Gradient Using Spatially Variable Electron Cyclotron Current Drives," Fusion Engineering & Design 192 (2023) 113914.

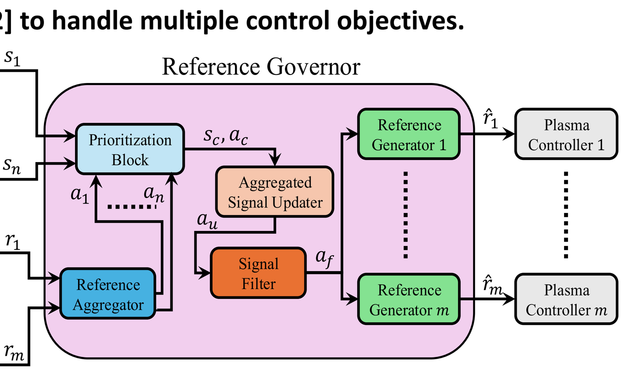
Stability Limit Avoidance by Reference Governors and Safe RL



Safe RL: Safety Penalty modifies Reward

- Reinforcement Learning (RL) offers a new path to designing controllers to regulate the plasma while avoiding stability limits
- Safe RL integrates safety constraints without the need of a stability-limit model
- Application example: RL agent trained using DDPG (Deep Deterministic Policy Gradient) in [1] to control DT density while avoiding reaching Greenwald Limit

- During plasma operation, disturbances can lead to violation of stability limits. Reference governors (RG) modify pre-optimized plasma control targets to ensure safety.
- Plasma controllers track the modified targets, ensuring stability limit adherence.
- A generic RG framework has been developed [2] to handle multiple control objectives.
- The RG takes reference and stability signals (model-based or data-driven)
- The RG aggregates references and compares them with stability limits
- On risk of violation, the RG adjust the most critical signal and filter it to remove high-frequency noise
- The filtered signal is split into safe references for each controller

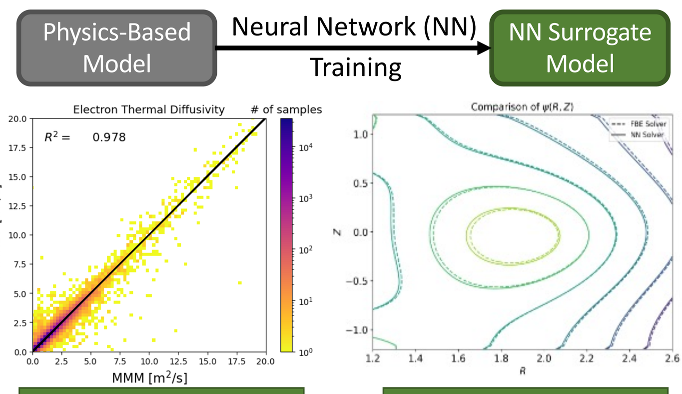


[1] S. T. Paruchuri et al. "Density regulation with disruption avoidance in next-generation tokamaks using a safe reinforcement learning-based controller," FED (2025).
[2] S. T. Paruchuri and E. Schuster. "Reference Governor for Plasma Scalar Control to Prevent Stability Limit Breaches in Tokamaks," IAEA FEC 2025 → Nuclear Fusion.

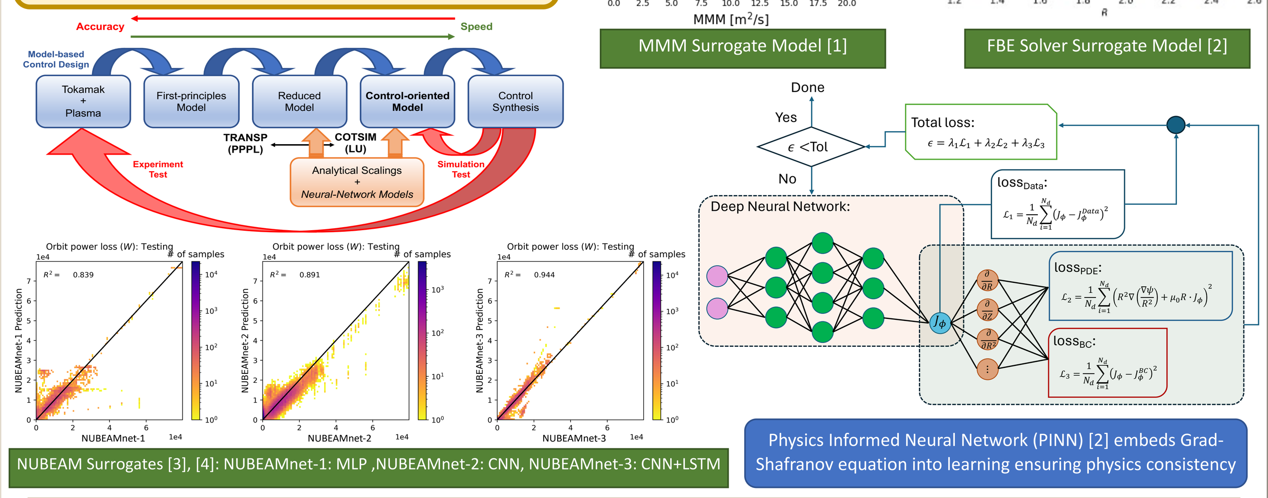
Surrogate Models: Fast+Accurate Prediction in Control Applications

- Control applications demand models:
  - Fast → Off–line applications
    - ✦ Closed-loop simulations
    - ✦ Model-based scenario optimization
  - Very fast → Real-time applications
    - ✦ Feedback control
    - ✦ Real-time optimization
    - ✦ Estimation & Forecasting
- Machine Learning (ML) models:
  - Fast + Accurate + Broadly Applicable

Physics-Based Model → Neural Network (NN) Training → NN Surrogate Model



MMM Surrogate Model [1] | FBE Solver Surrogate Model [2]

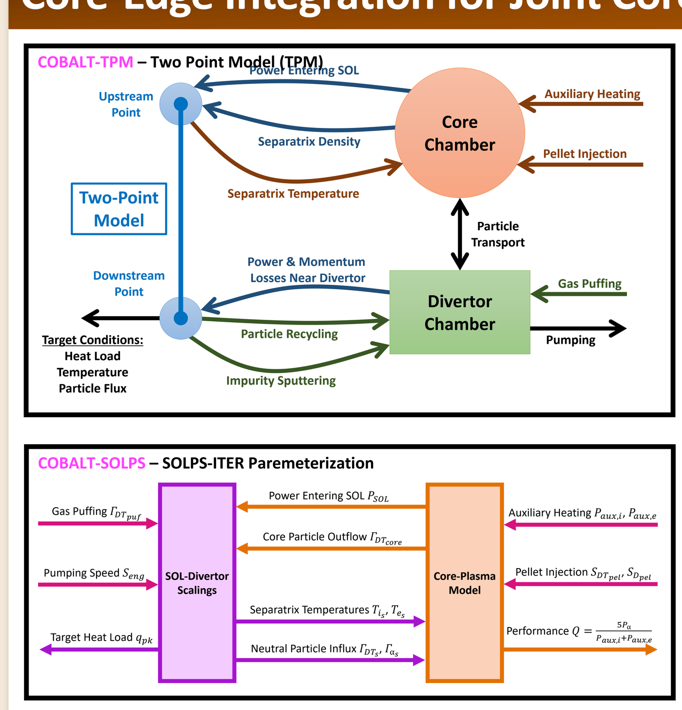


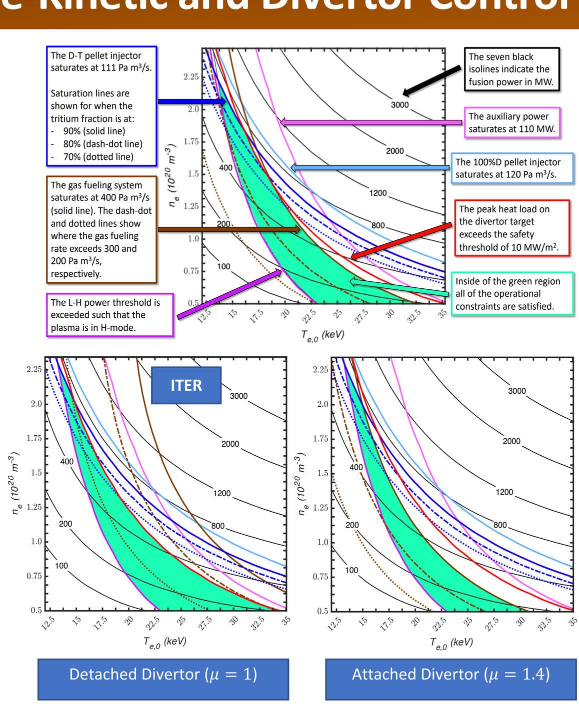
NUBEAM Surrogates [3], [4]: NUBEAMnet-1: MLP ,NUBEAMnet-2: CNN, NUBEAMnet-3: CNN+LSTM

Physics Informed Neural Network (PINN) [2] embeds Grad-Shafranov equation into learning ensuring physics consistency

[1] K. Shabbir et al., "MMMnet: A Neural Network Surrogate for Real-Time Transport Prediction Based on the Updated Multi-Mode Model," Plasma 8, no. 3: 32, 2025.
[2] Z. Wang et al., "Neural-network-based Free-boundary Equilibrium (FBE) Solver to Enable Fast Scenario Simulations," IEEE Transactions on Plasma Science, 2024.
[3] Z. Wang et al., "Neural Network Model of Neutral Beam Injection on EAST to Enable Fast Transport Simulations," Fusion Engineering and Design 191 (2023) 113514.
[4] Z. Wang et al., "NUBEAM Surrogate Models Based on MLP, CNN and Parallel CNN-LSTM Neural Network Architectures ," IAEA-FEC, London, UK, 2023.

Core-Edge Integration for Joint Core-Kinetic and Divertor Control





Detached Divertor (μ = 1) | Attached Divertor (μ = 1.4)

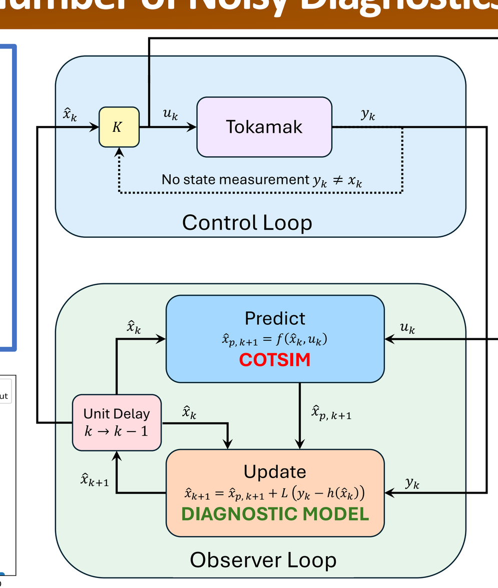
- Core-edge coupling: Integrated burn/divertor control
  - SOL conditions → Wall recycling & impurity pollution
  - Core Fusion power → Power across separatrix on divertor
  - High target heat loads ($q_{peak} > 10\ MW/m^2$) → Melting
  - Two modeling paths: COBALT-TPM [2], COBALT-SOLPS [3]
- COTSIM-TPM & COTSIM-SOLPS under development

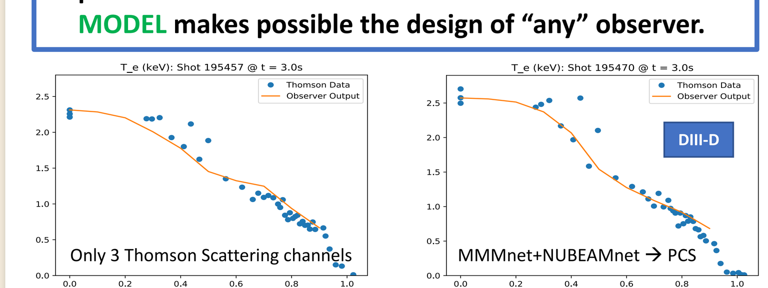
- ✦ Safe divertor heat load → primary obstacle towards accessing regimes with higher fusion power output
- ✦ Tritium fraction drops → ITER operable space shrinks
- ✦ Normalized neutral pressure (μ) ↑ (detached → attached) → ITER operable space shrinks (lower fusion power output)
- ✦ Attached divertor: Gas injection rate (brown) limits access to high-fusion regimes before divertor heat load (red)

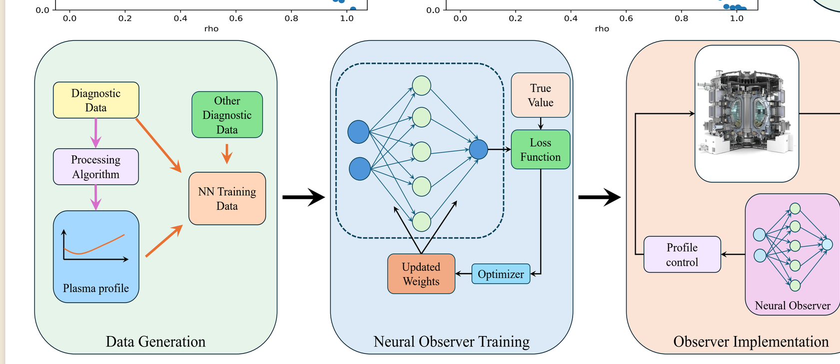
[1] V. Graber et al., "Control-Oriented Core-SOL-Divertor Model to Address Integrated Burn/Divertor Control Challenges in ITER," FED 192 (2023) 113635.
[2] V. Graber et al., "Assessment of Burning-Plasma Operational Space in ITER by Using a Control-Oriented SOLPS Parameterized Core-Edge Model," IAEA-FEC 2023.

Plasma State Estimation From Limited Number of Noisy Diagnostics

- Real-time plasma-state estimation is challenging due to noise and reduced number of diagnostics in reactors.
- Observer filters measurement "noise" not consistent with known physics (model → Physics-based COTSIM).
- Challenge is to design gain L to make $\hat{x} \to x$ (good estimation). L regulates tradeoff between model prediction & measurement. COTSIM + DIAGNOSTIC MODEL makes possible the design of "any" observer.







- Neural observers provide alternative path to state estimation & forecasting
- Observers can also be designed for sensor, actuator, plant fault detection & isolation, as well as for model parameter estimation [2]

[1] S. Morosohk and E. Schuster, "Real-time Estimation of the Electron Temperature Profile in DIII-D by Leveraging NN Surrogate Models," CPP 2023, e202200153.
[2] C. Xu, Y. Ou, E. Schuster, "Transport Parameter Estimations of Plasma Transport Dynamics Using the Extended Kalman Filter," IEEE TPS, vol. 38, no. 3, March 2010.