Real-time reconstruction, control and optimization of plasma profiles using the RAPTOR code

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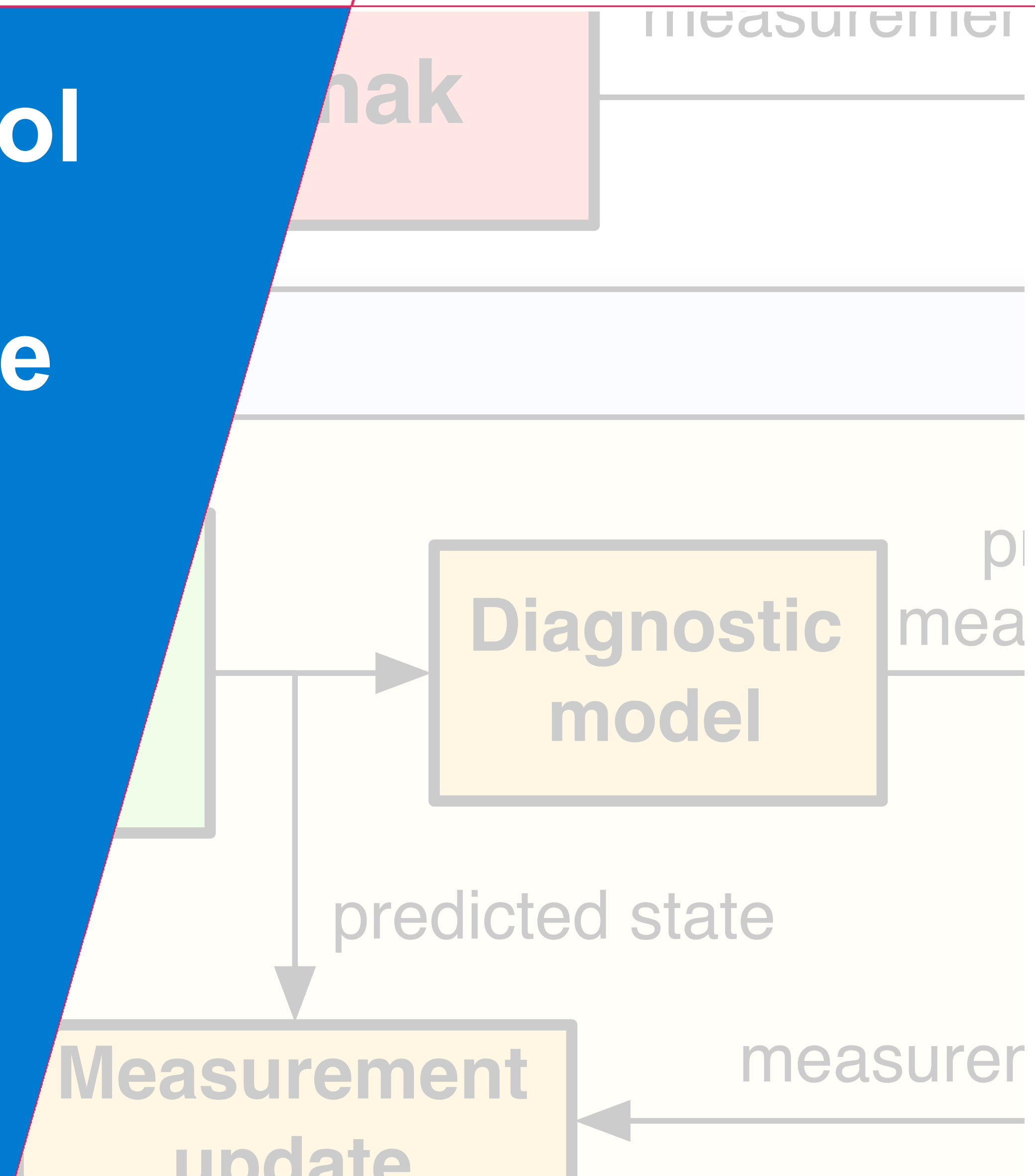

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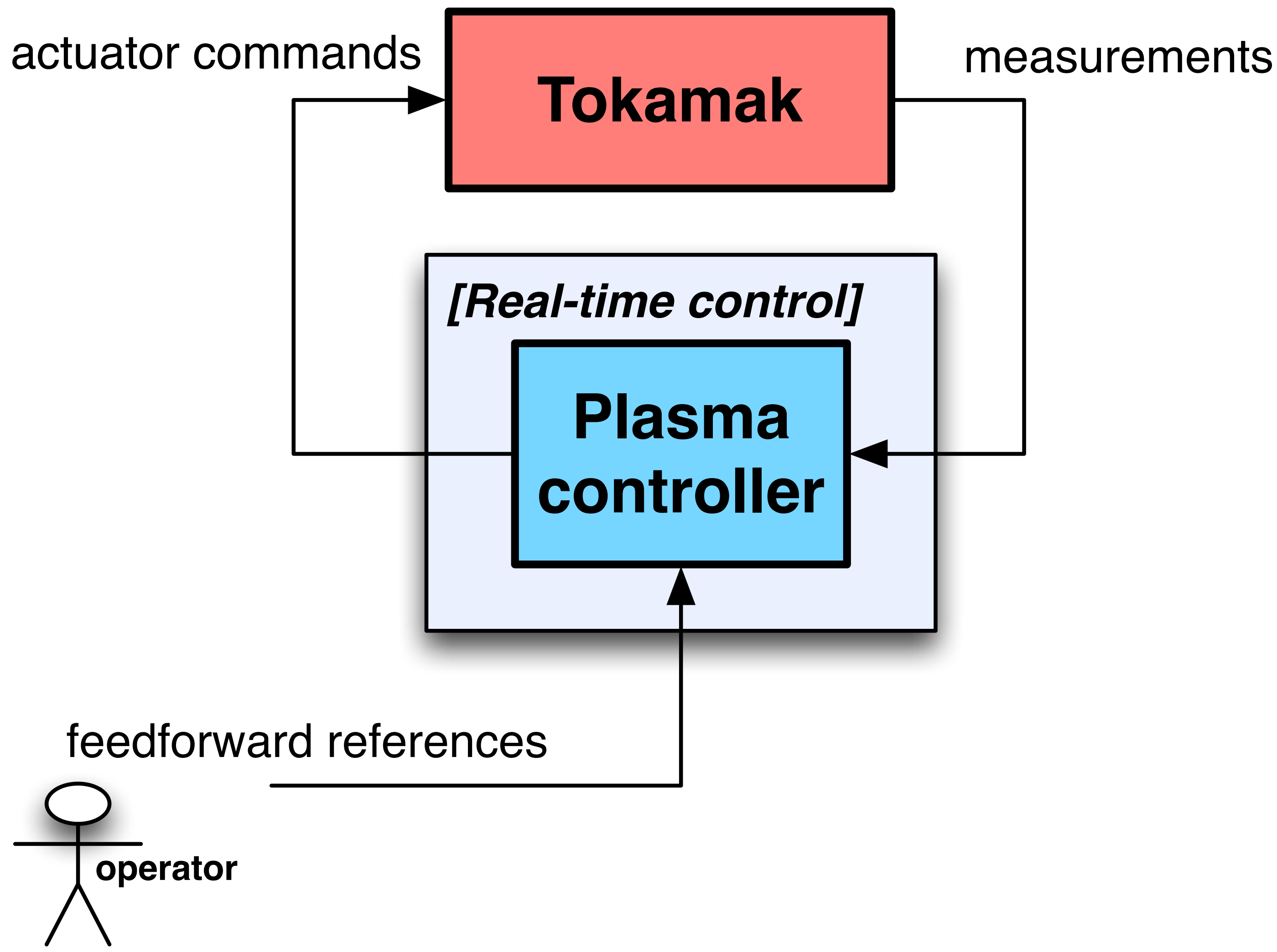
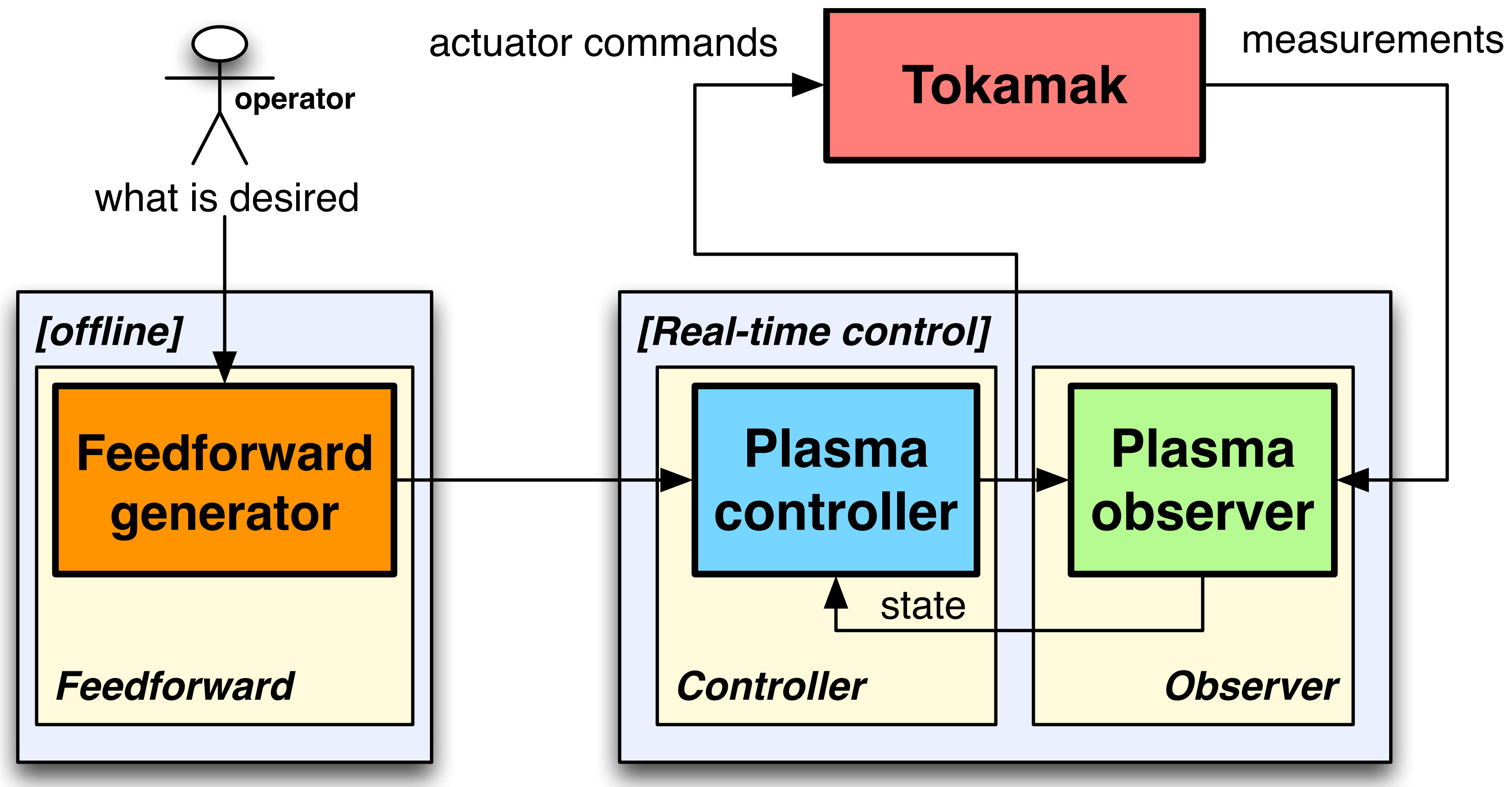
2nd ISM working Session 2013 CEA Cadarache, France

Where innovation starts

Most control loops as used in tokamaks today



Model-based control system: components



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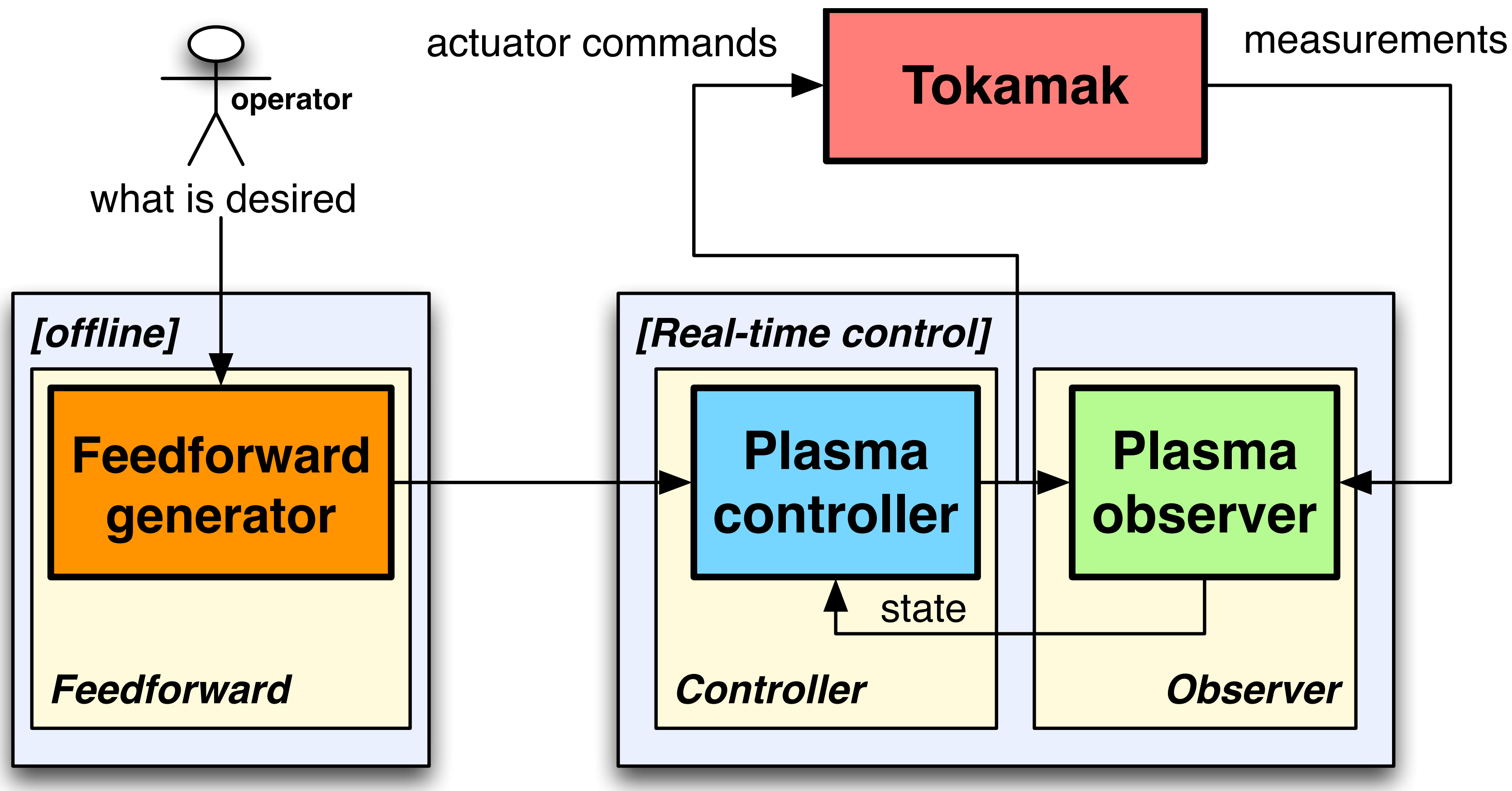

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  - **Appropriate when measurements are noisy and/or incomplete**

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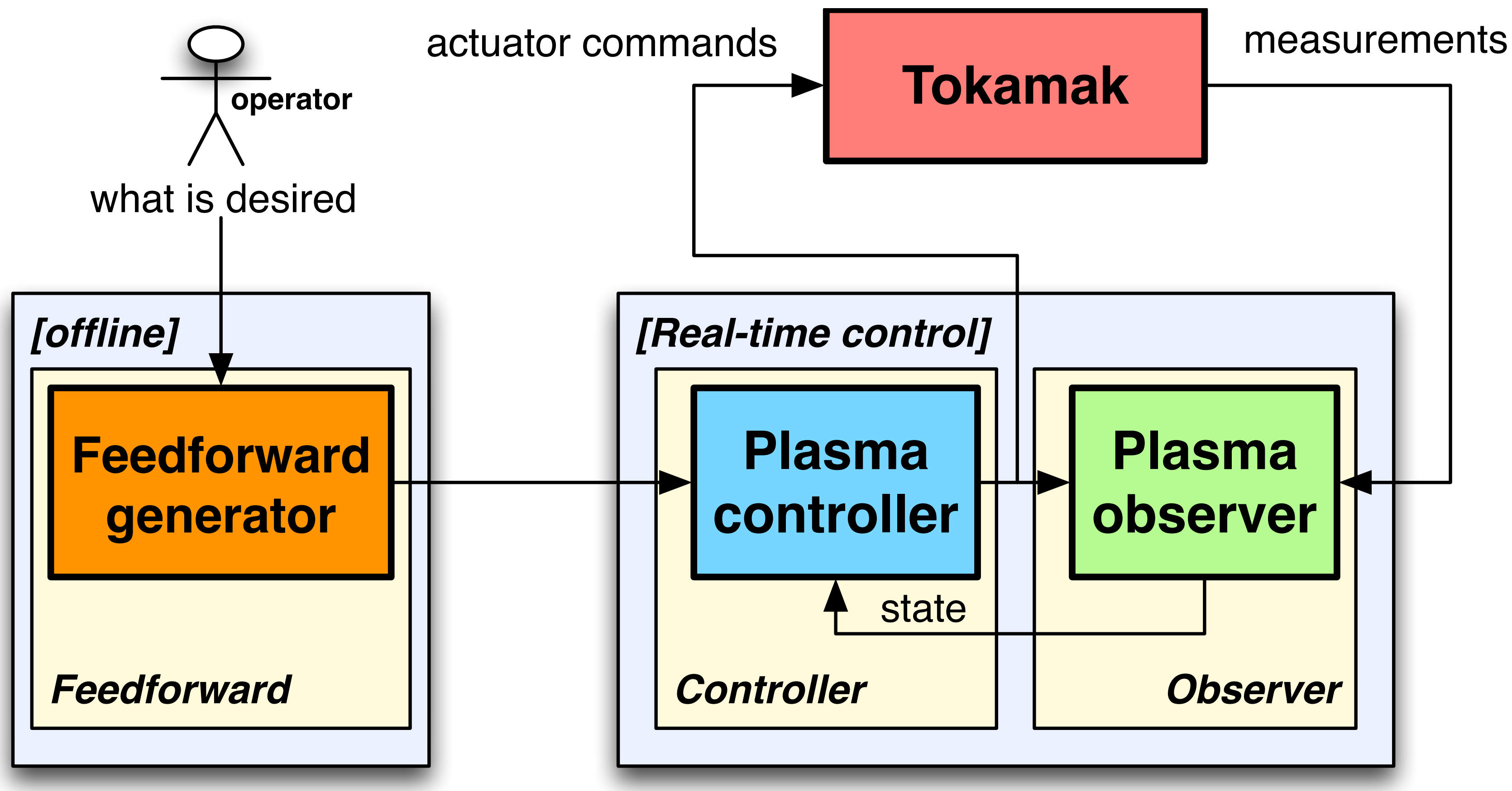

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- Automatic generation of feedforward trajectories
  - Layer of abstraction for operators

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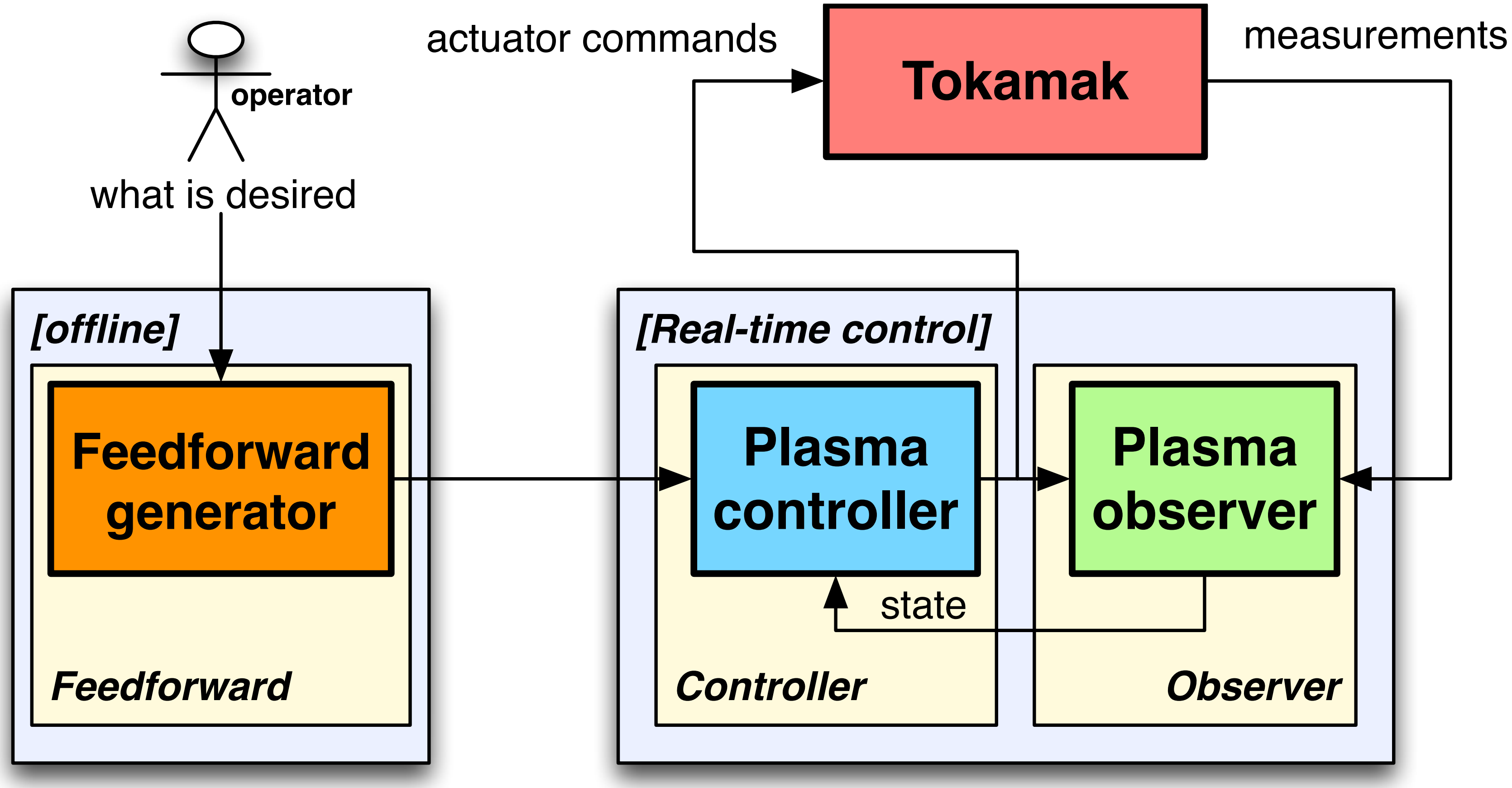

- **State estimation (observer) separate from state control**
  - **Appropriate when measurements are noisy and/or incomplete**
- **Automatic generation of feedforward trajectories**
  - **Layer of abstraction for operators**
- **Model-based plasma controller**
  - **Use model to predict the future and determine best control strategy**

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Models for model-based control

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- **Use first-principle models deeply embedded in design and implementation of real-time control**
  - **What models? not full physics models, but *control-oriented* models.**
    - **Capability to run in real-time (or faster)**
    - **Capture main dynamics and coupling, but no perfection needed**

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- **This talk: Presentation of new control-oriented code RAPTOR (Rapid Plasma Transport Simulator)**
  - **Features**
  - **Applications**
    - ***Fast simulator for rapid scenario development, controller design, ...***
    - **Profile reconstruction**
    - **Trajectory optimization**
    - **Real-time feedback control and prediction**

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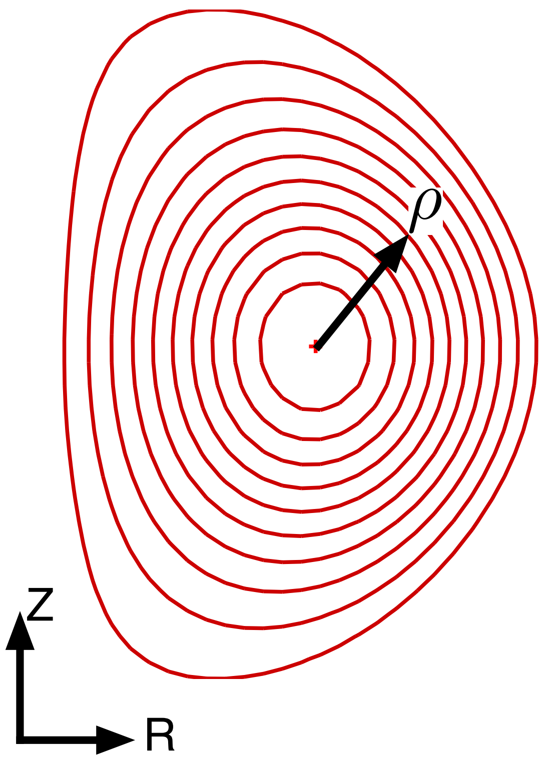
RAPTOR code contains key nonlinear couplings affecting the dynamics of profile evolution

- **Noncircular, axisymmetric, fixed poloidal flux surface shape**
- **1D, (flux surface averaged) poloidal flux diffusion**

$$\sigma_{||}\frac{\partial\psi}{\partial t} = \frac{R_0 J^2}{\mu_0\rho}\frac{\partial}{\partial\rho}\left(\frac{G_2}{J}\frac{\partial\psi}{\partial\rho}\right) - \frac{V'}{2\pi\rho}(j_{BS}+j_{ext})$$

  - **Neoclassical conductivity & bootstrap : Sauter-Angioni**



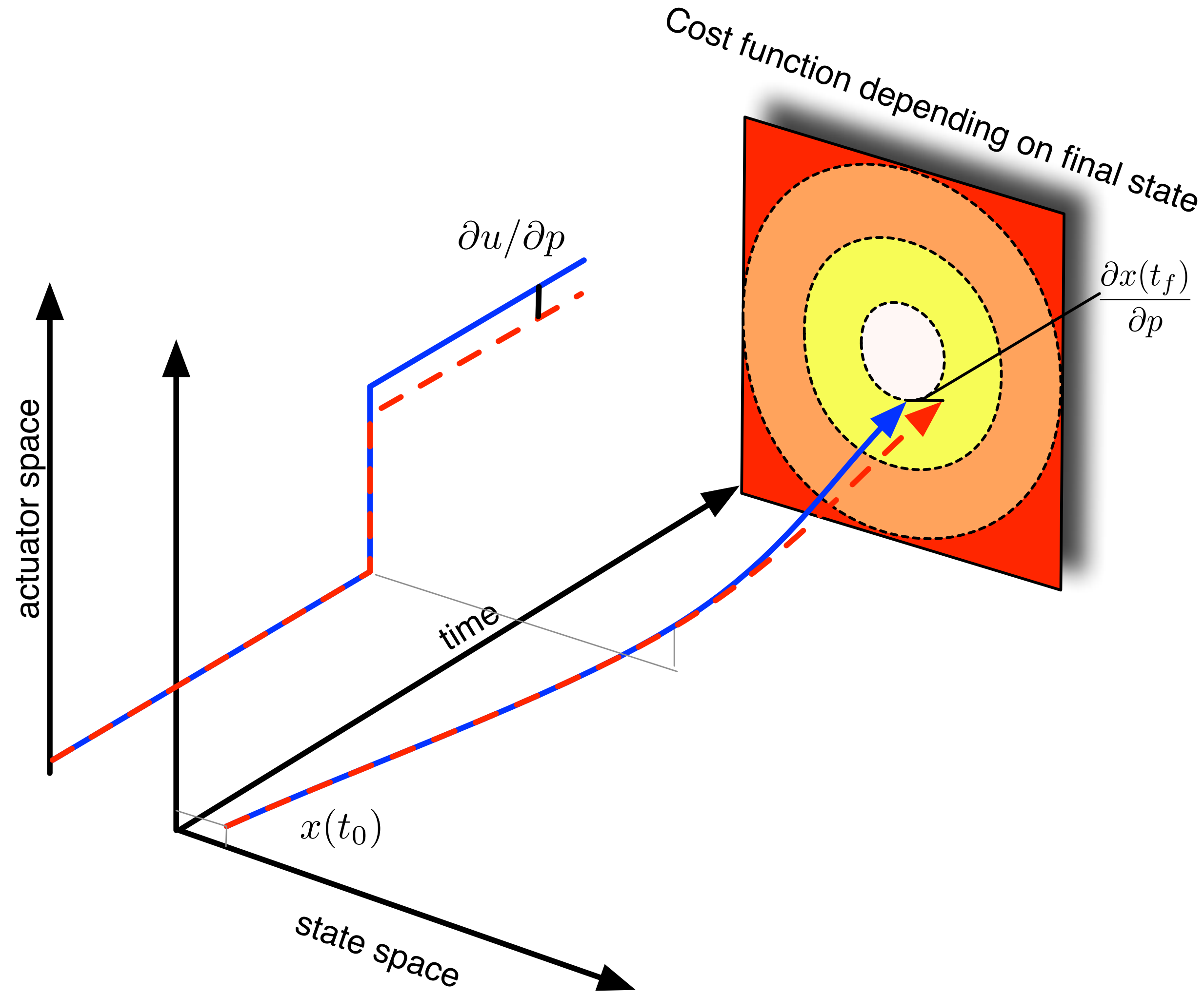
- **Electron temperature diffusion**

$$V'\frac{\partial}{\partial t}[n_e T_e] = \frac{\partial}{\partial\rho}G_1 V' n_e \chi_e \frac{\partial T_e}{\partial\rho} + V' P_e$$

  - **Prescribed density profile evolution, T_i= k*T_e**
  - **Ad-hoc analytical model for thermal diffusivity**
- **Sources**
  - **Parametrized model for EC deposition**
  - **Pencil beam model for NBI (P. Geelen)**
  - **Alpha particle, radiation, brehmsstr. included (J. van Dongen)**

RAPTOR uses implicit solver which calculates Jacobians at all times, gives local linearization

- **Numerics:**
  - Cubic spline finite elements
  - Fully implicit, full Newton steps
  - Analytic Jacobians for all terms
  - few ms per time step
- **Gradients computed using forwards sensitivity method**
  - State sensitivities: *dx/dp* at all times.
  - Linearization of the profile dynamics around the profile trajectory - local linear model
  - Important for numerical optimization and controller design
- **Model parameter optimization**
  - Automatically based on experimental data - new work by P. Geelen (to be submitted)



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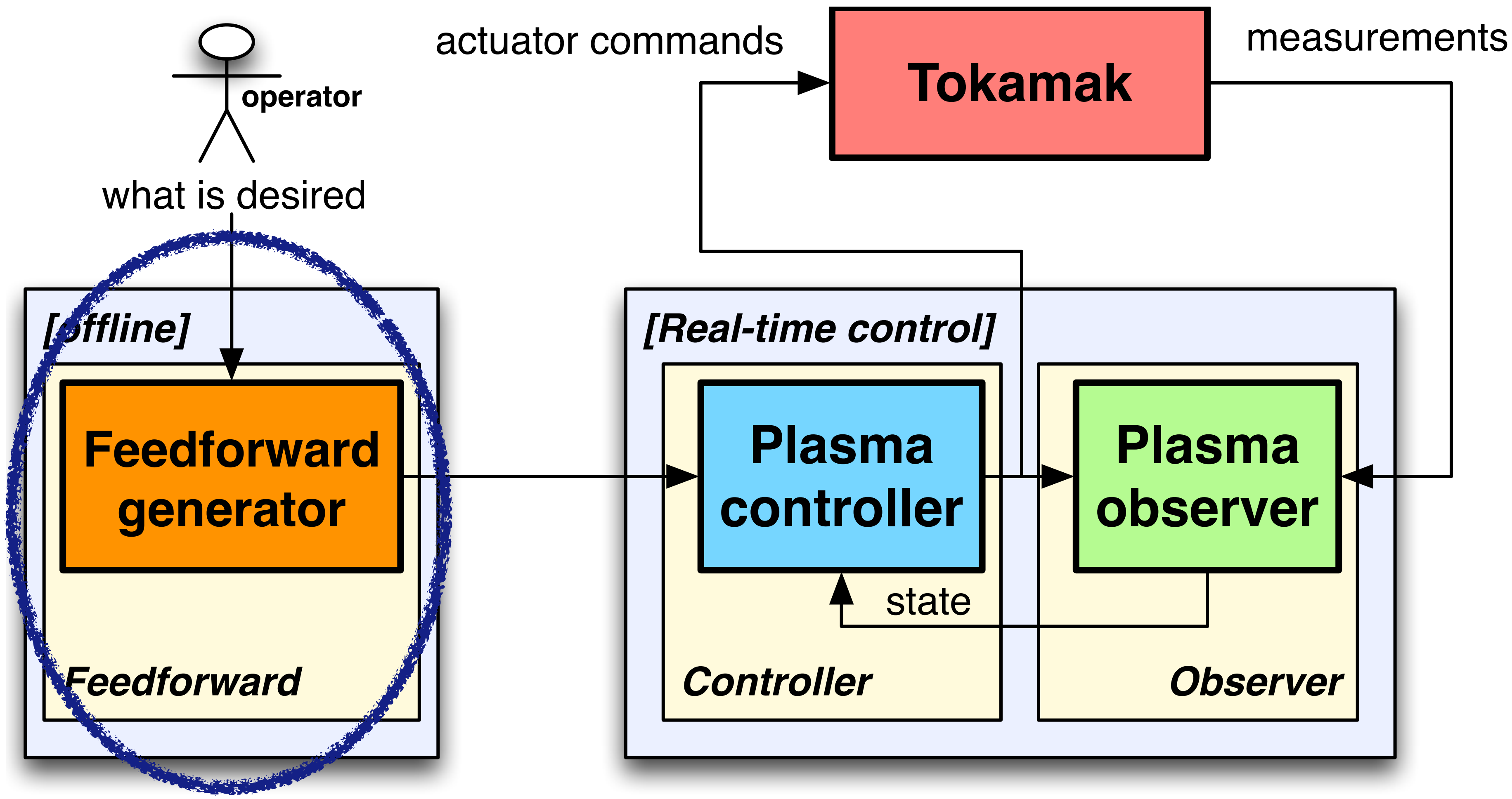
operator
what is desired
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Tokamak
measurements
[offline]
Feedforward generator
Feedforward
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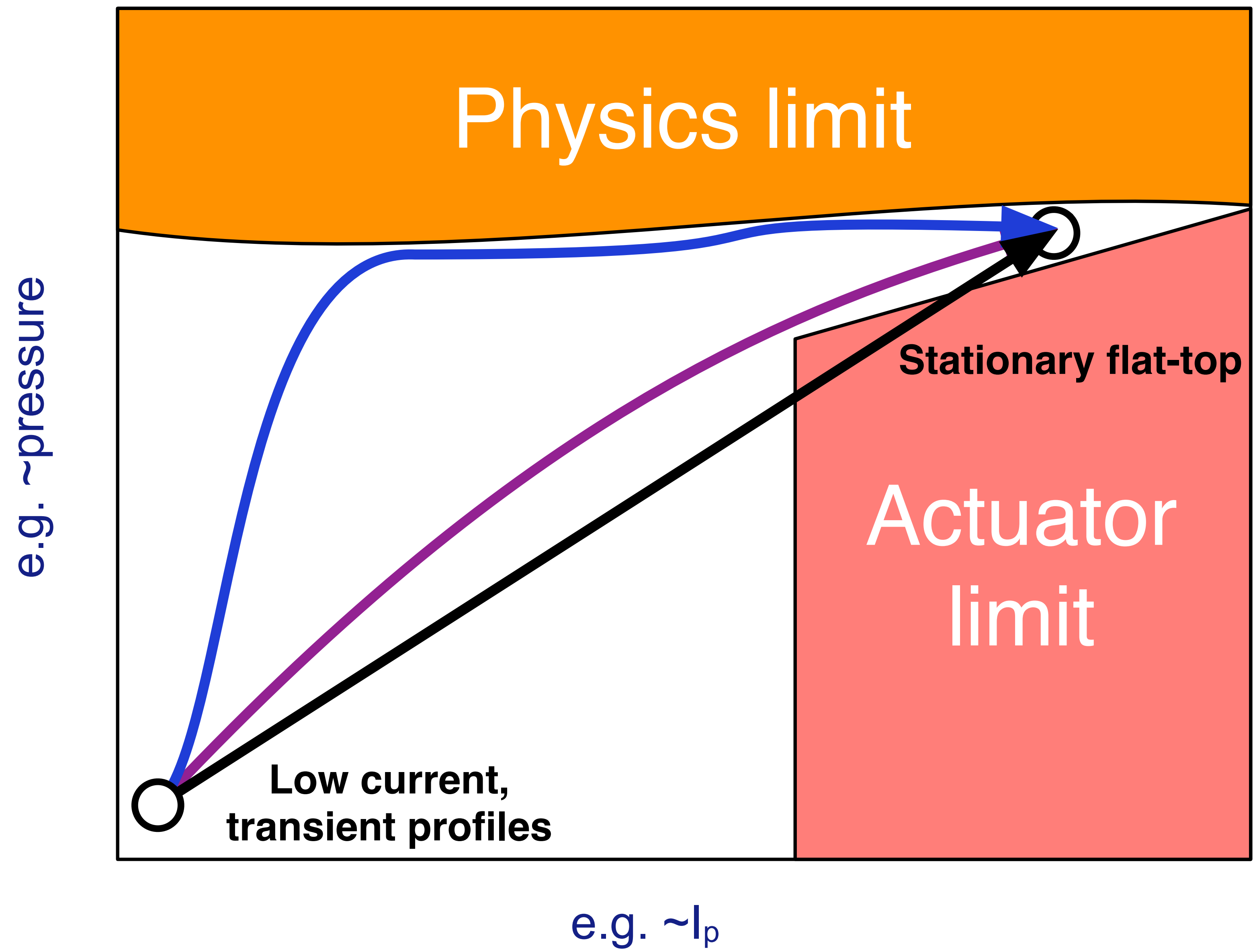
Plasma controller
Plasma observer
state
Controller
Observer

Model-based optimization of open-loop actuator trajectories

Tokamak operational space

Which route to take?



Optimization problem: ingredients

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- **Cost function *J*: reflects desired properties of plasma**
  - **Weighted sum of several profile-dependent terms**
    - **distance from target profiles (q, T_e, $E_{||}$...)**
    - **Flux consumption (for longer pulse)**
    - **Stationarity (for relaxed profiles - flat loop voltage)**

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  - **sum of basis functions P(t) (piecewise linear,constant,...)**

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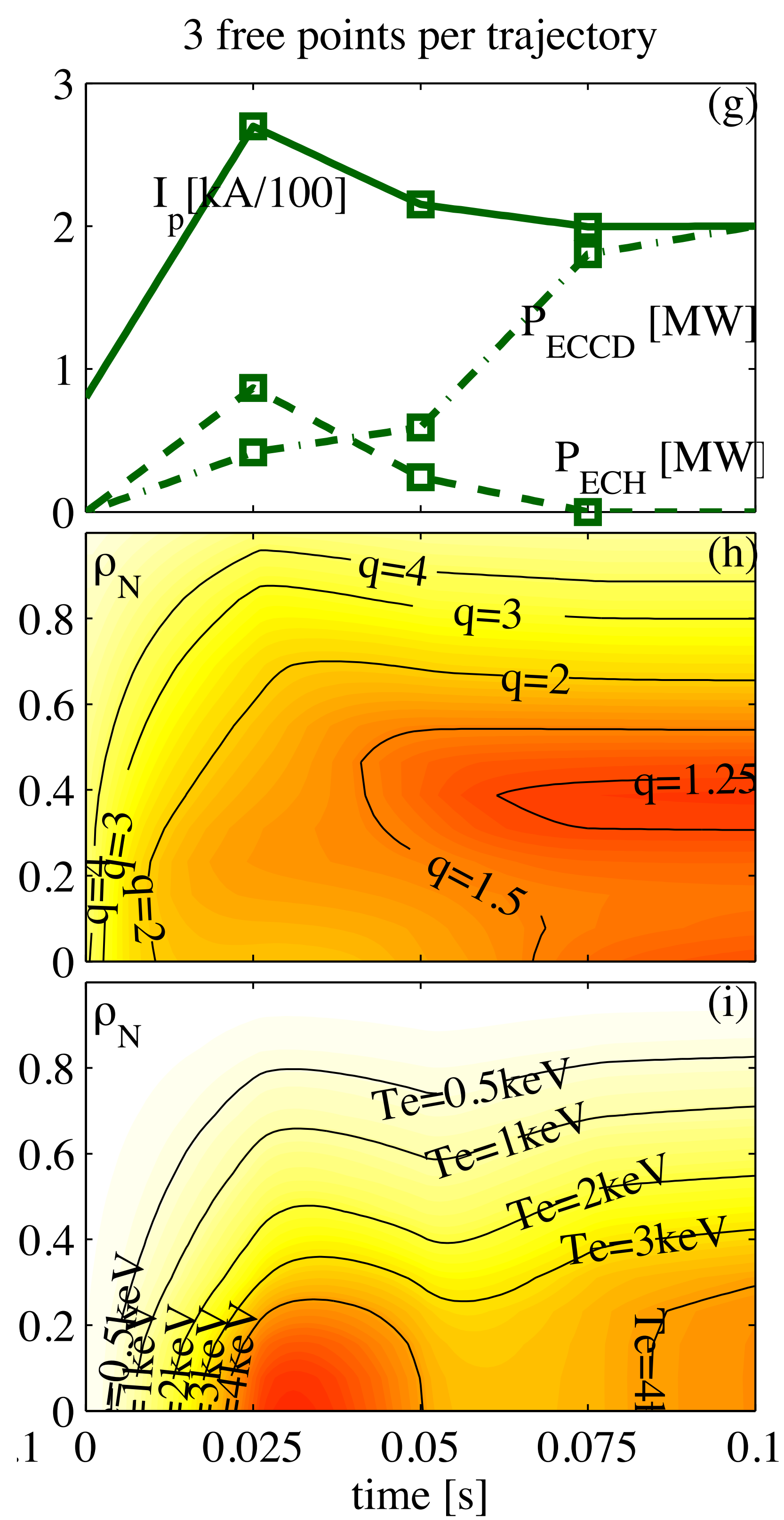
- **Problem: find *p* minimizing *J(p)*, satisfying *C(p)***
- **Solution: Sequential Quadratic Programming**
  - **Gradients dJ/dp dC/dp are *known,* this greatly speeds up computations.**

Results for ramp up to ‘hybrid’ q profile show benefit of early heating and I_p overshoot



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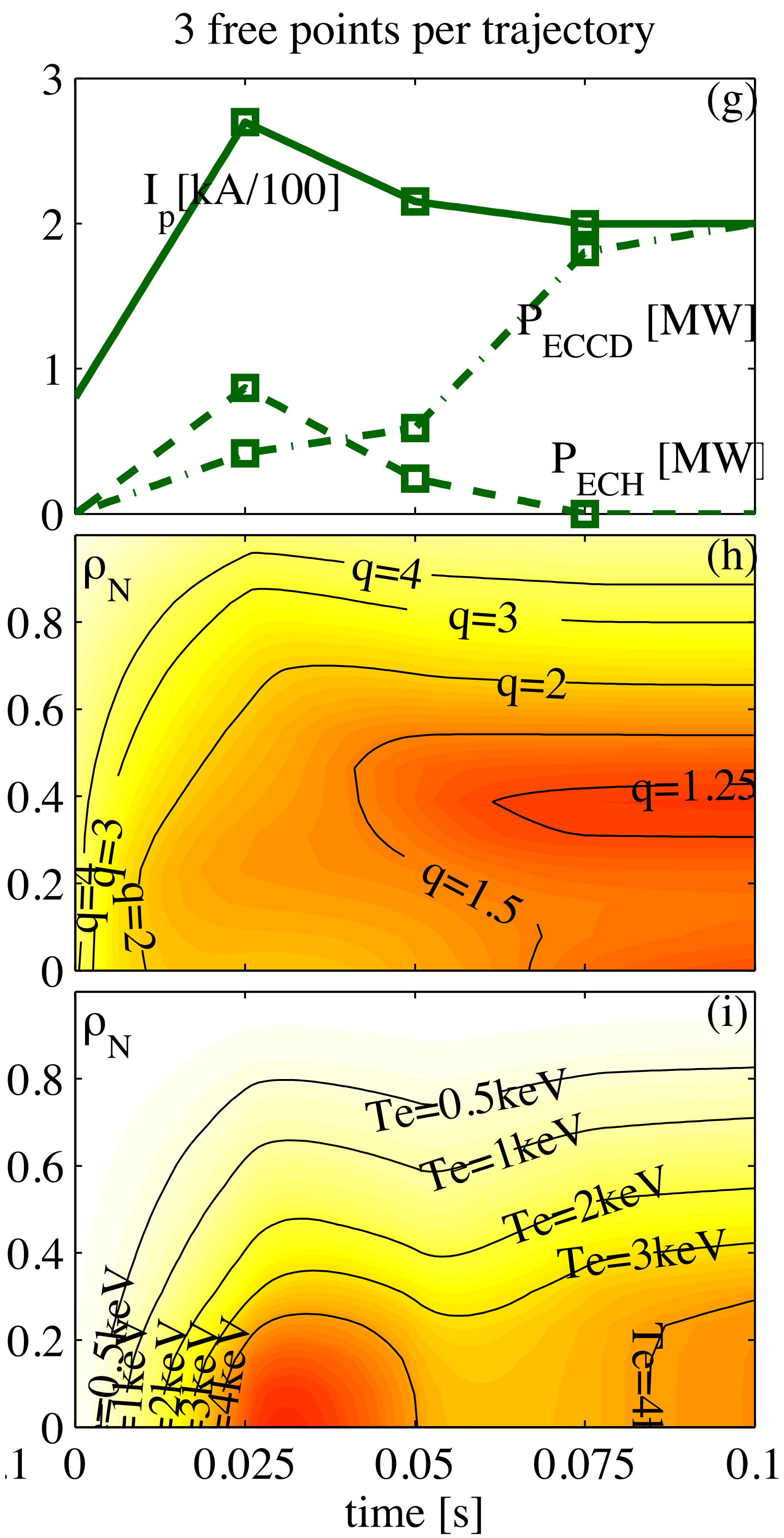

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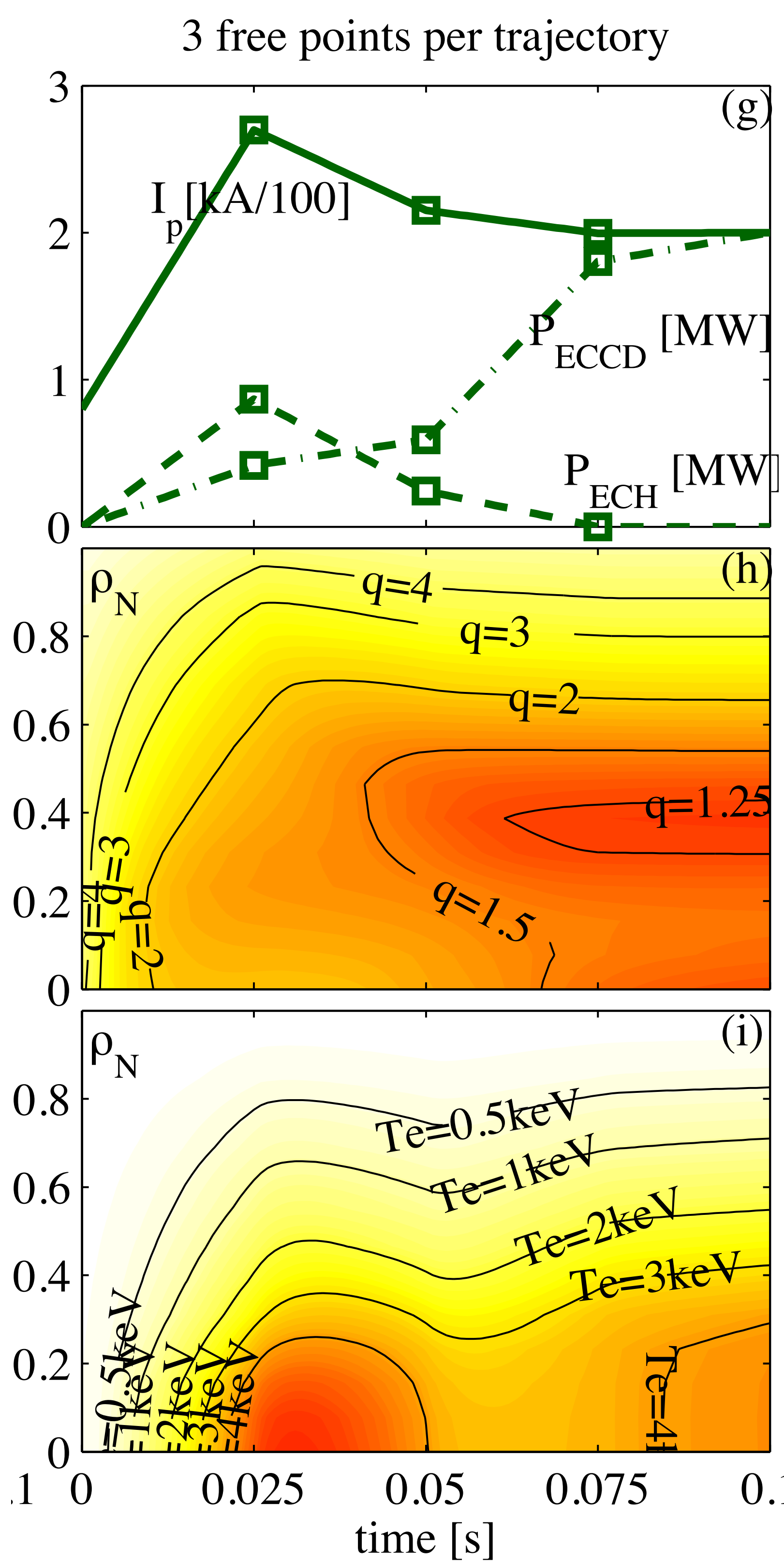

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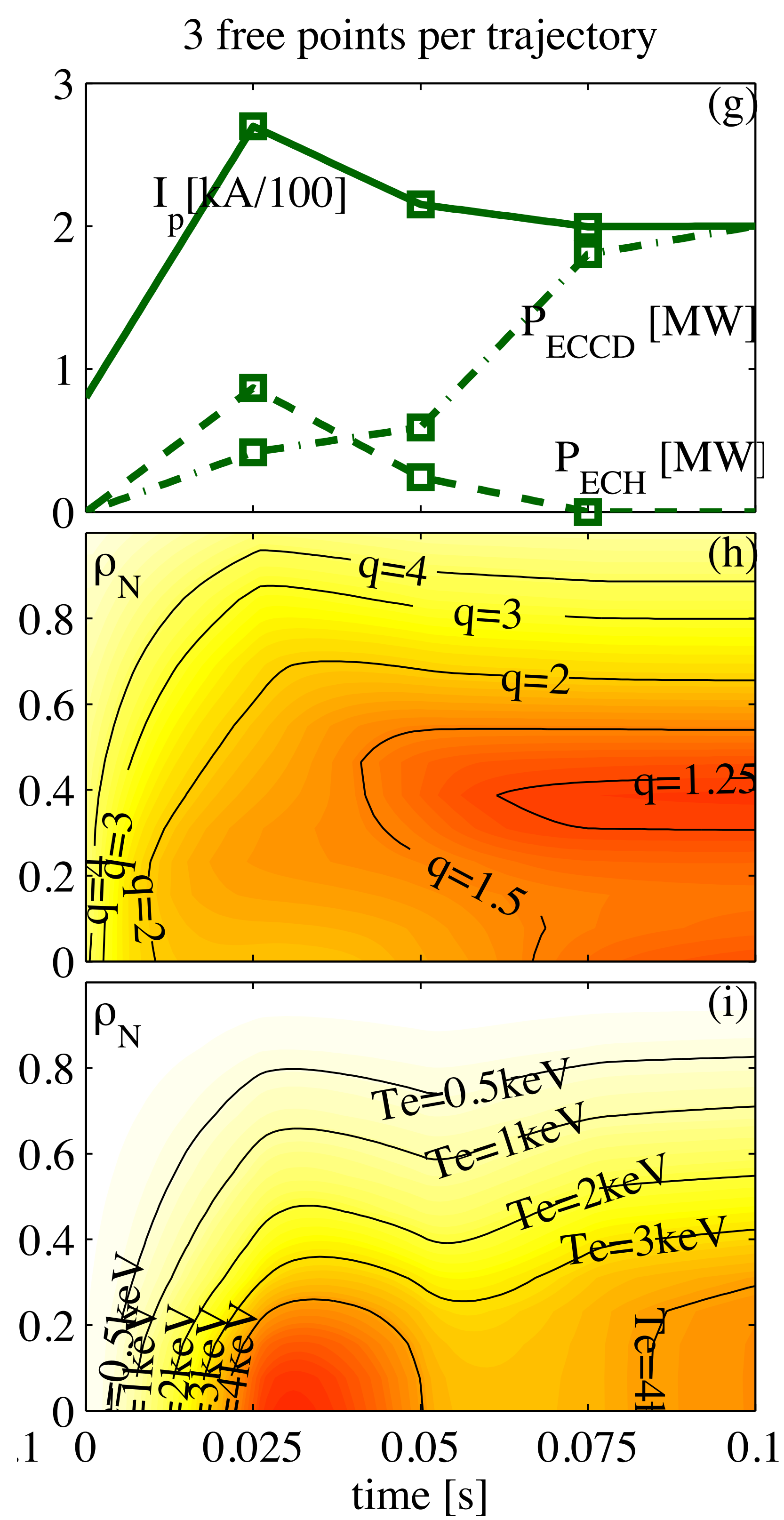

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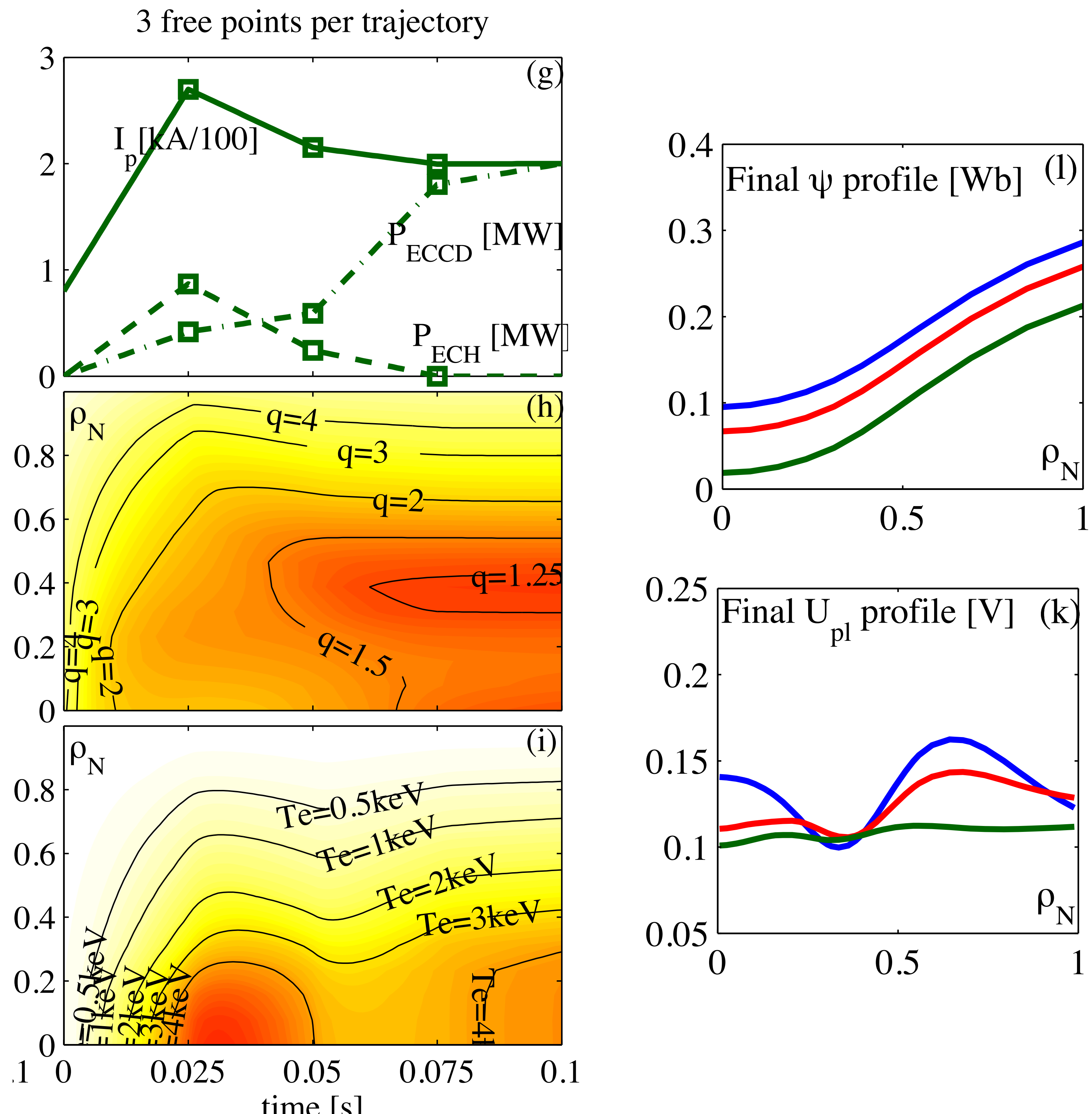
- **Multiple constraints**
- **Result:**
  - Lower flux cons.
  - Flatter U_{pl} profile



Perspectives and future plans for trajectory optimization

- **Optimization of ramp-up**
  - First applied to simulated TCV ramp-up [F. Felici PPCF 2012]
  - Recently applied to ITER hybrid scenario simulations (see next talk by J. van Dongen)
  - Validation of optimized ramp-up trajectories in existing tokamaks envisaged
- **Optimization of ramp-down ?**
  - Appropriate cost functions/constraints?
  - Optimal (varying?) I_p rampdown rate
  - Timing removal of different heating/cd actuators accounting for profile dynamics?
  - Need to take shape evolution into account ?
  - Provide guidelines to experiments and simulations: save valuable time

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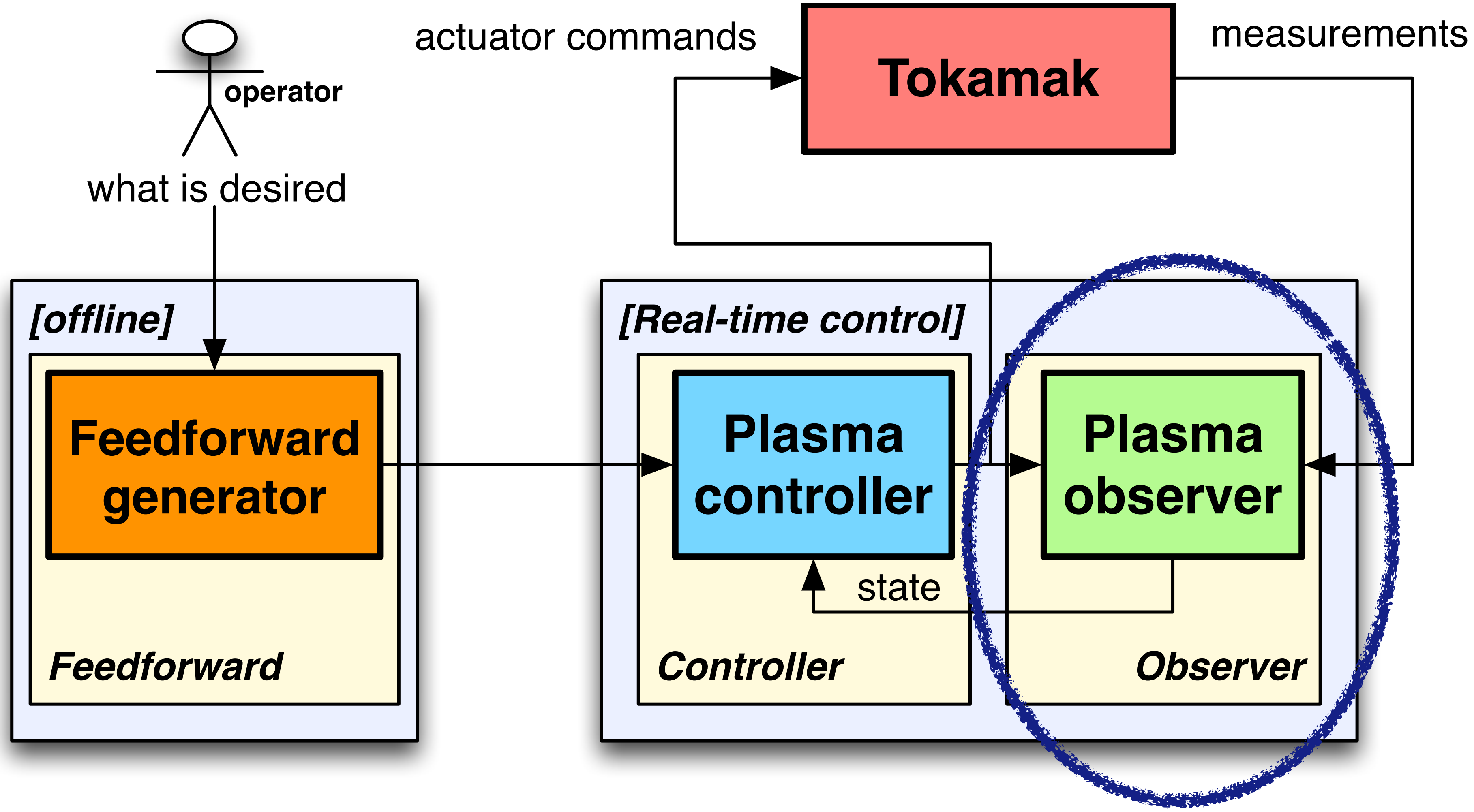

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- **In the past: feed measurements directly to plasma controller**
- **Today: constrained equilibrium reconstruction for some controlled quantities (e.g. shape, q), direct feedback for others (e.g. density)**
  - **Drawbacks:**
    - **Accuracy constrained by diagnostics, limited set of basis functions.**
    - **Does not use knowledge of previous time: each time step is an independent fitting problem.**
  - **But: we run post-shot interpretative transport simulations to analyze shots in detail, measurements often included in ad hoc fashion.**

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    - Does not use knowledge of previous time: each time step is an independent fitting problem.
  - But: we run post-shot interpretative transport simulations to analyze shots in detail, measurements often included in ad hoc fashion.
- Model-based plasma state reconstruction, merge model prediction and diagnostic measurements
  - Amounts to performing a *real-time, measurement constrained simulation* of the plasma time evolution.
    - Known in control literature as *dynamic state observer*, or *Kalman filter.*
    - Widely used in robotics, image processing, broad literature exists

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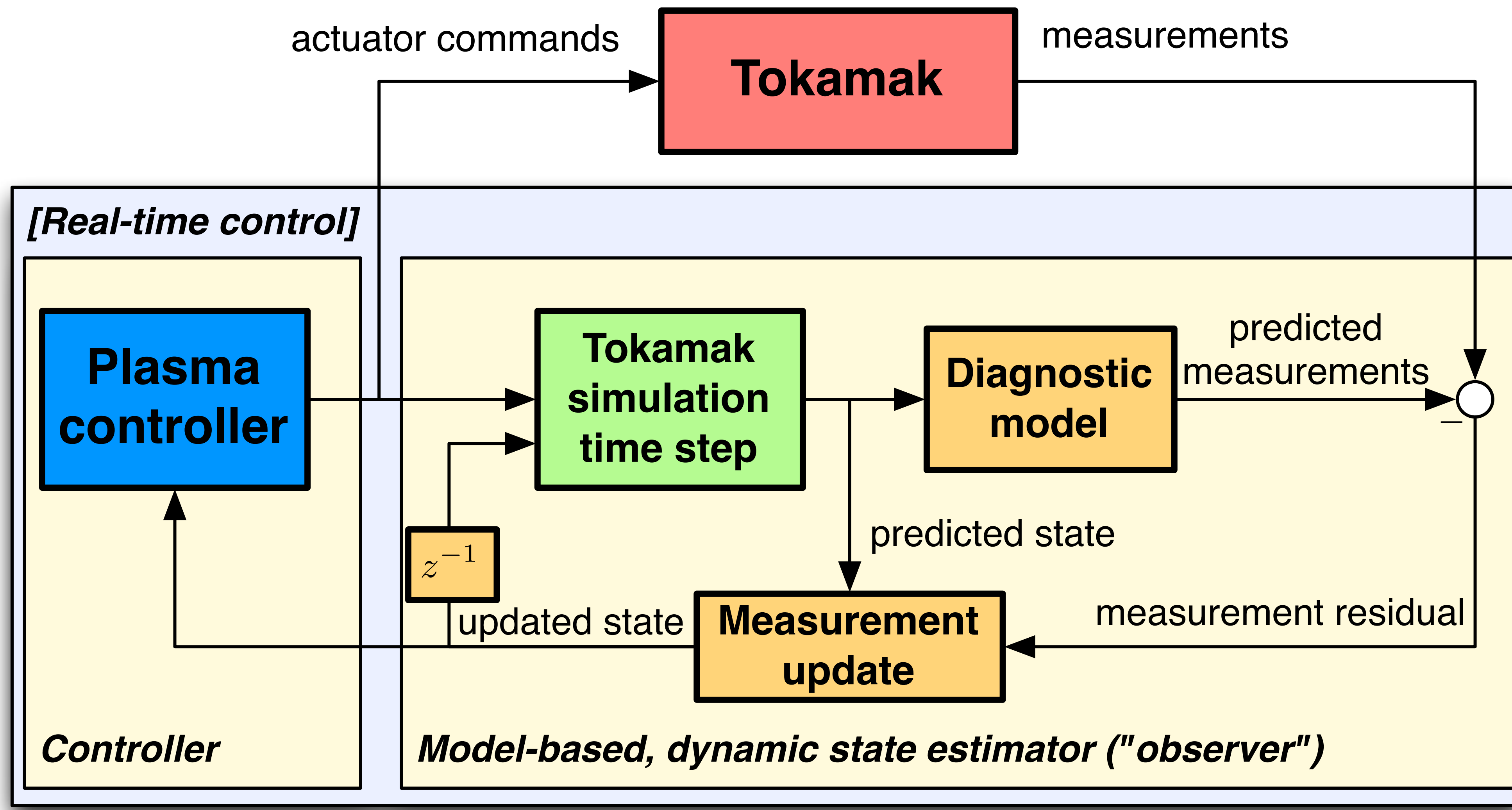
Predict next plasma state with model, correct by diagnostic measurements

- **Components of model-based state observer**
  - **Forward simulator (predict state one step ahead)**
  - **Diagnostic model (predict measurements from predicted state)**
  - **Measurement update (correct state based on actual measurements)**



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State observer

- **Full state knowledge means *everything,* not just what you measure.**
  - **q, shear, Te, dTe/drho, j_{aux}, j_{bs}, j_{oh} profiles**
  - **Confinement time, non-inductive current fraction, H-factor, ...**

- **Measurement update law reflects confidence in models vs measurements**
  - **Diagnostic noise?**
    - **Filtered out naturally by model: accept only variations consistent with model time scales.**
  - **Disturbances / faults ?**
    - **Detect systematic disturbances of measured evolution w.r.t. model**
    - **Classify as normal (e.g. model mismatch) or off-normal (e.g. imminent disruption)**

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  - Classification of model errors, faults, disruption signatures.

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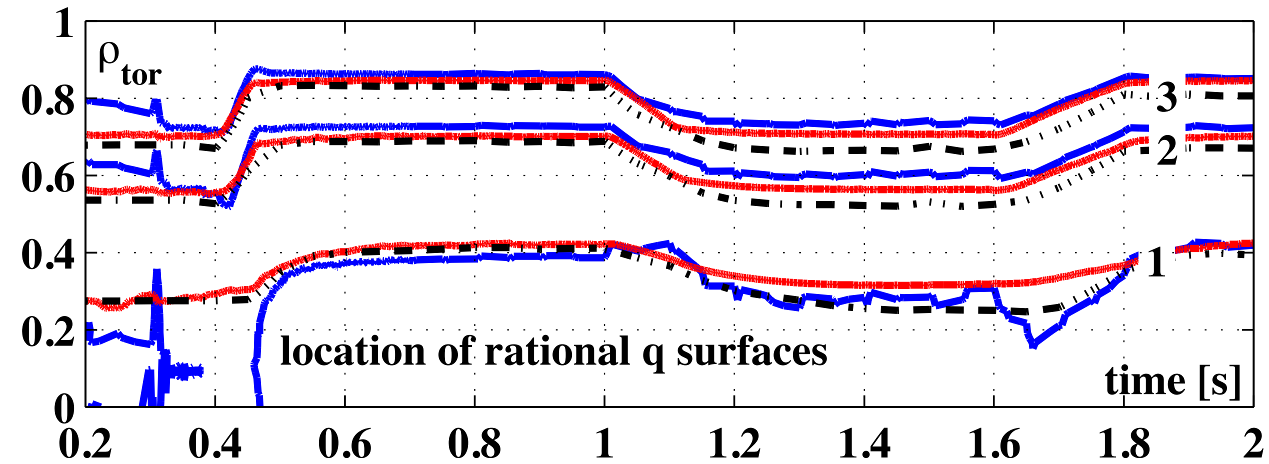
Pilot implementation done on TCV, ASDEX-Upgrade implementation underway

- **Pilot RAPTOR implementation solves flux diffusion equation in real-time on TCV real-time control system**
  - **Kinetic profiles from real-time diagnostics**
  - **[F. Felici et al, NF2011]**



- **ASDEX-Upgrade implementation**
  - **Flux and T_e evolution, ~3ms per time step**
  - **Real-time meas. update for Te from ECE**
  - **First results at EPS2013**

- **ITER simulation proof-of-principle**
  - **Work to do for this week**

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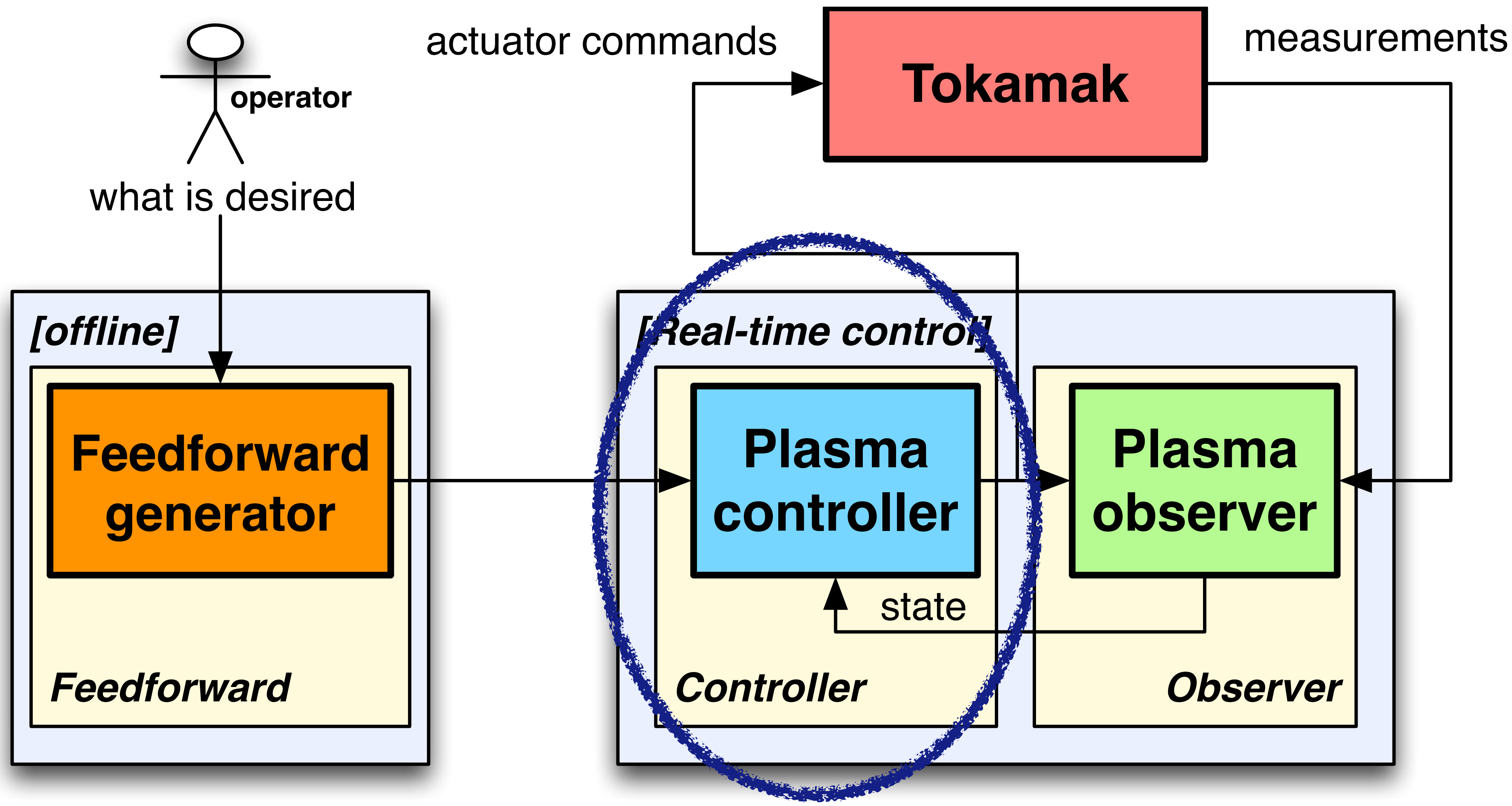
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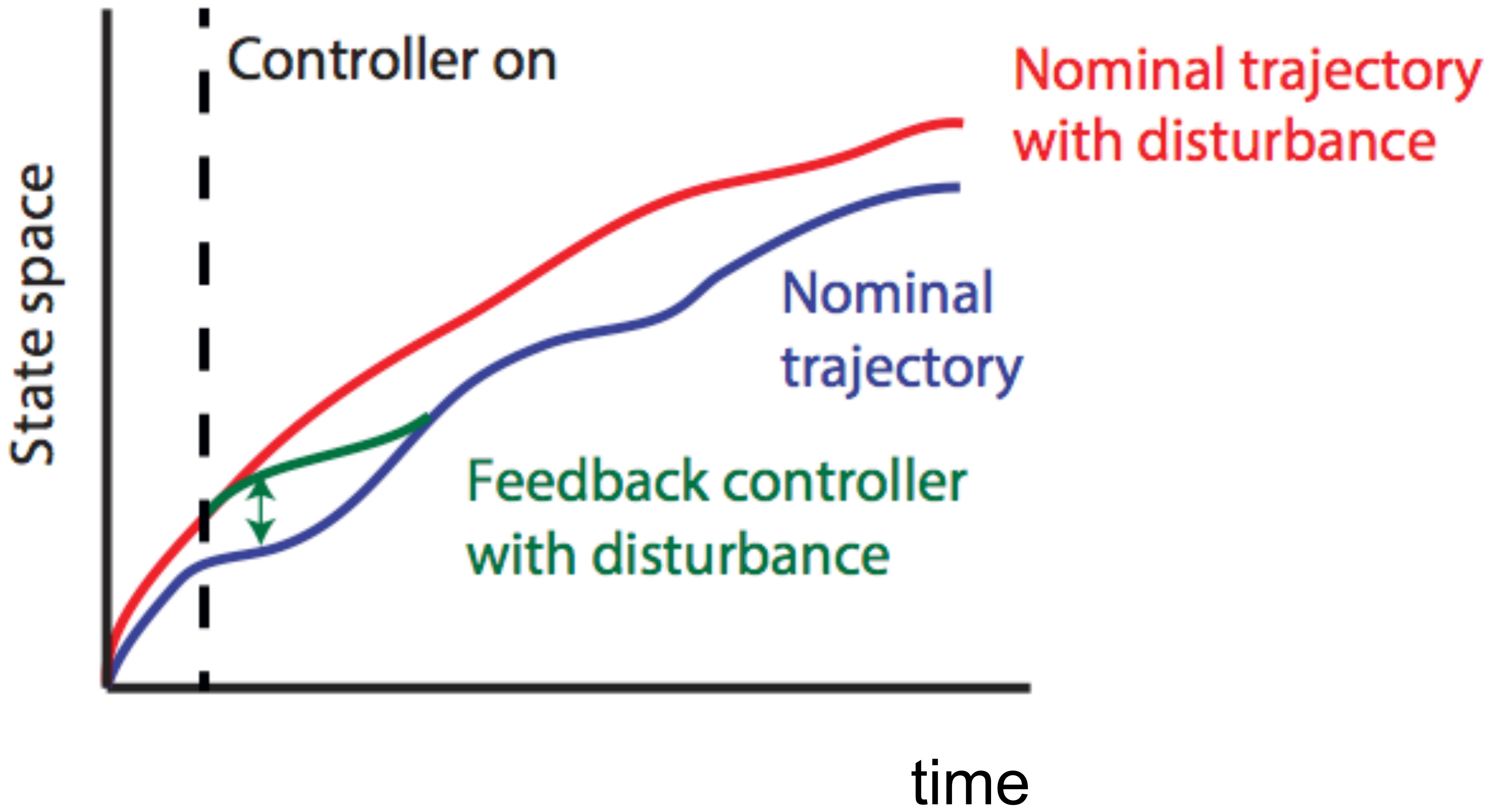
Feedback control around nominal trajectory, knowing expected variation of profile dynamics



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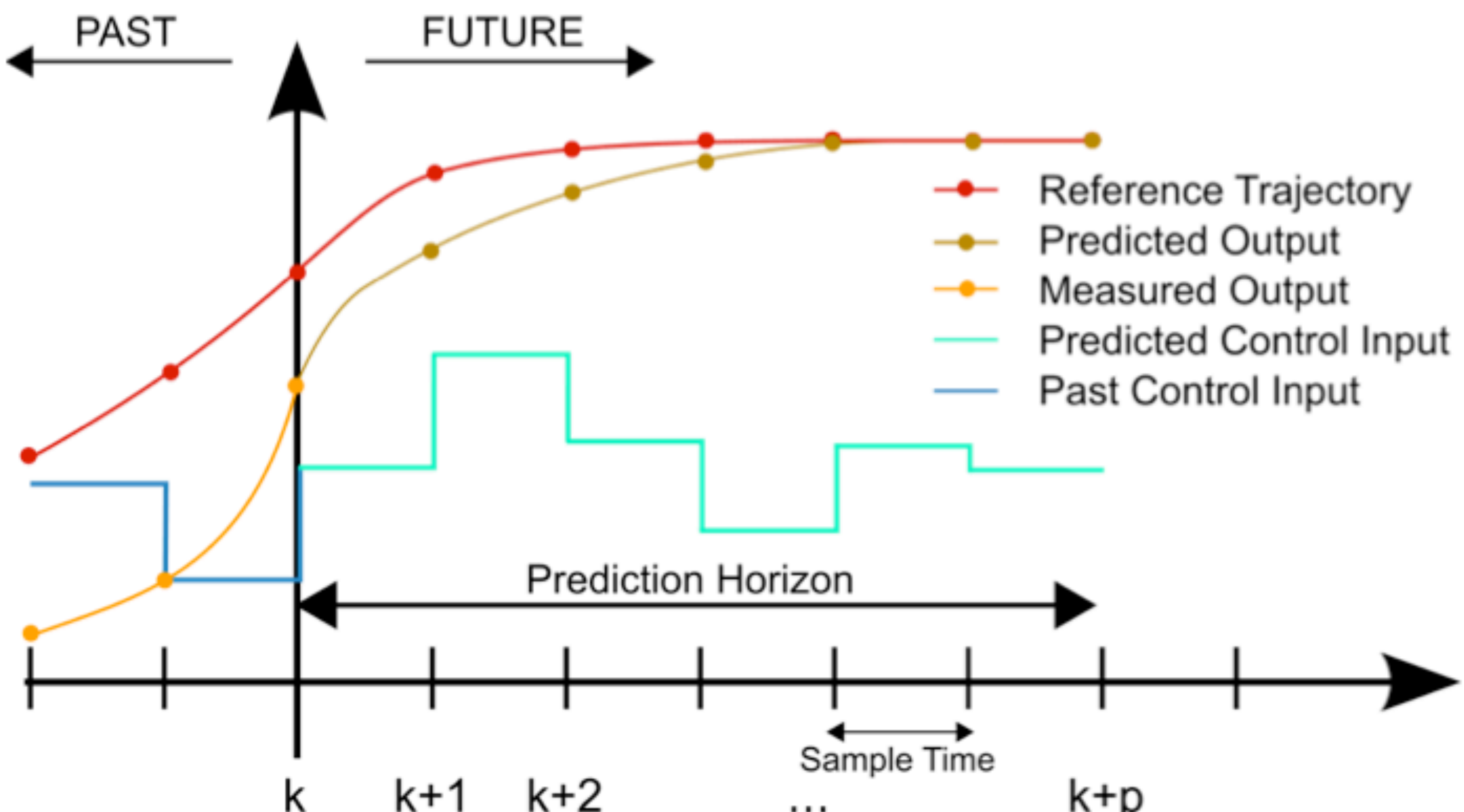
Model predictive control: determine optimal future actuator trajectory to go back to reference

- Real-time prediction of plasma profile trajectory “for free”
- Naturally include (varying) constraints for state and actuator
- Early warning if constraints can not be met (disruption pred.)



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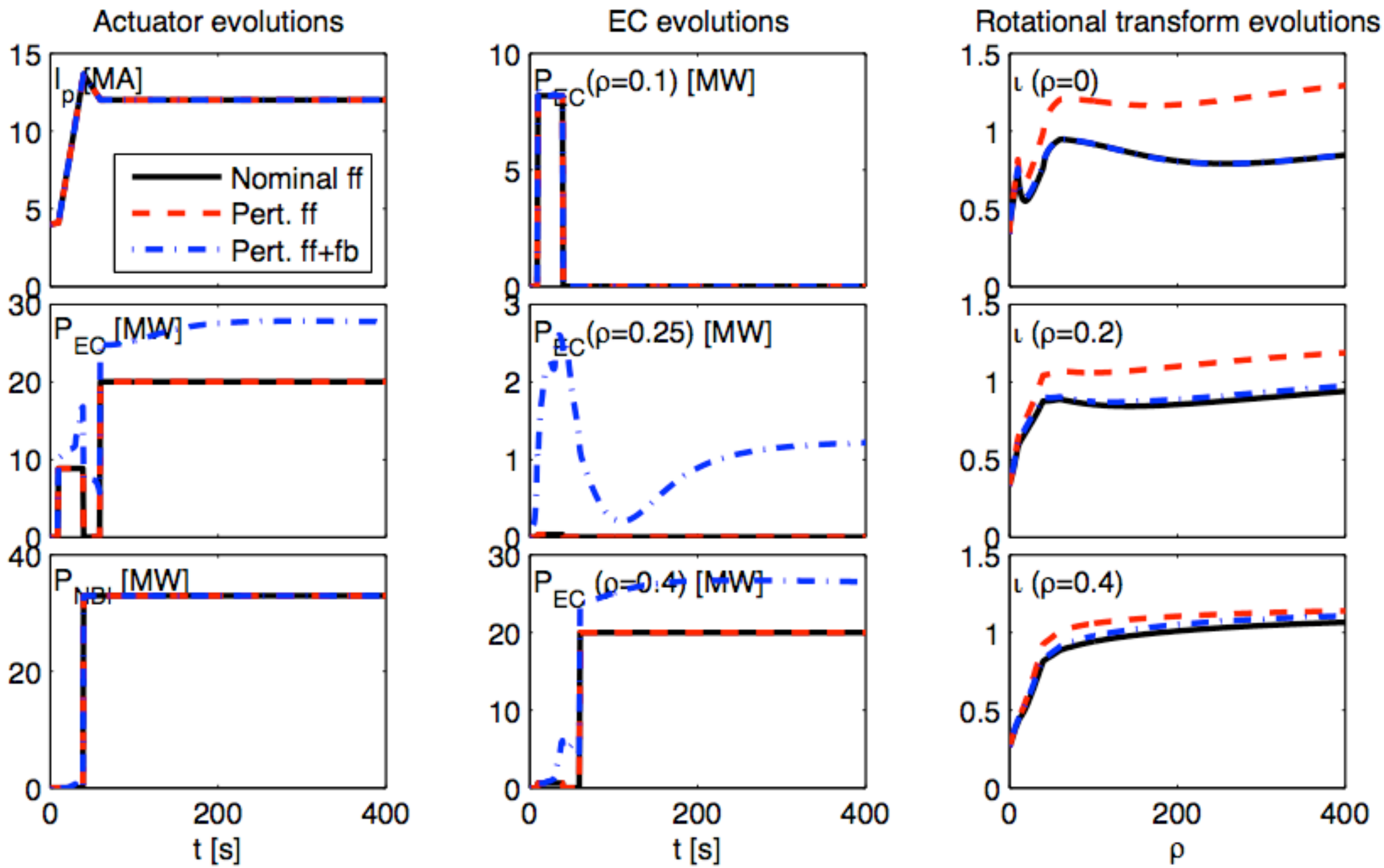
First results for ITER hybrid scenario show feedback control with model errors, disturbances

- **Work by Bert Maljaars (TU/e), to be presented at EPS2013**



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Conclusions

- RAPTOR: plasma profile evolution code for real-time control, reconstruction & optimization
  - Key nonlinearities captured in time-evolution
- Model-based optimization of actuator trajectories
  - Numerically compute feedforward trajectories for ramp-up to and ramp-down from flattop.
- Model-based plasma state reconstruction
  - Provides a natural framework to merge diagnostic measurements with model predictions.
- Model-based predictive control
  - Look into the future, control if you can, give warning if you can not
- More details in the literature:
  - [F. Felici, PPCF (2012) 025002]
  - [F. Felici, Nuclear Fusion (2011) 083051]
  - [F. Felici, EPFL Thesis 5203, Lausanne, Switzerland] http://dx.doi.org/10.5075/epfl-thesis-5203

Thank you

Backup slides

Parameter sensitivity of profile evolution

- **Time evolution depends on mode parameters**
  - **One example: a transport model parameter**
  - **Another example: a parameter defining the input trajectory**

$$\tilde{f}(x_{k+1}, x_k, u_k) = \tilde{f}_k = 0 \; \forall \; k$$

- **Differentiating with respect to parameter *p*, we get the *sensitivity equation***

$$0 = \frac{\mathrm{d}\tilde{f}_k}{\mathrm{d}p} = \frac{\partial \tilde{f}_k}{\partial x_{k+1}} \frac{\partial x_{k+1}}{\partial p} + \frac{\partial \tilde{f}_k}{\partial x_k} \frac{\partial x_k}{\partial p} + \frac{\partial \tilde{f}_k}{\partial u_k} \frac{\partial u_k}{\partial p} + \frac{\partial \tilde{f}_k}{\partial p}$$

  - **Linear ODE for dx_k/dp, solve while evolving nonlinear PDE: *Forward sensitivity analysis***
  - **Jacobians df_k/dx_k, df_k/dx_{k+1} are known from Newton iterations**
  - **Computational cost proportional to *p***
- **dx_k/dp gives the linearization of the state trajectories in the parameter space**

$$T_e(\rho, t)|_{p=p_0+\delta p} \approx T_e(\rho, t)_{p_0} + \frac{\partial T_e}{\partial x} \frac{\partial x}{\partial p} \delta p$$

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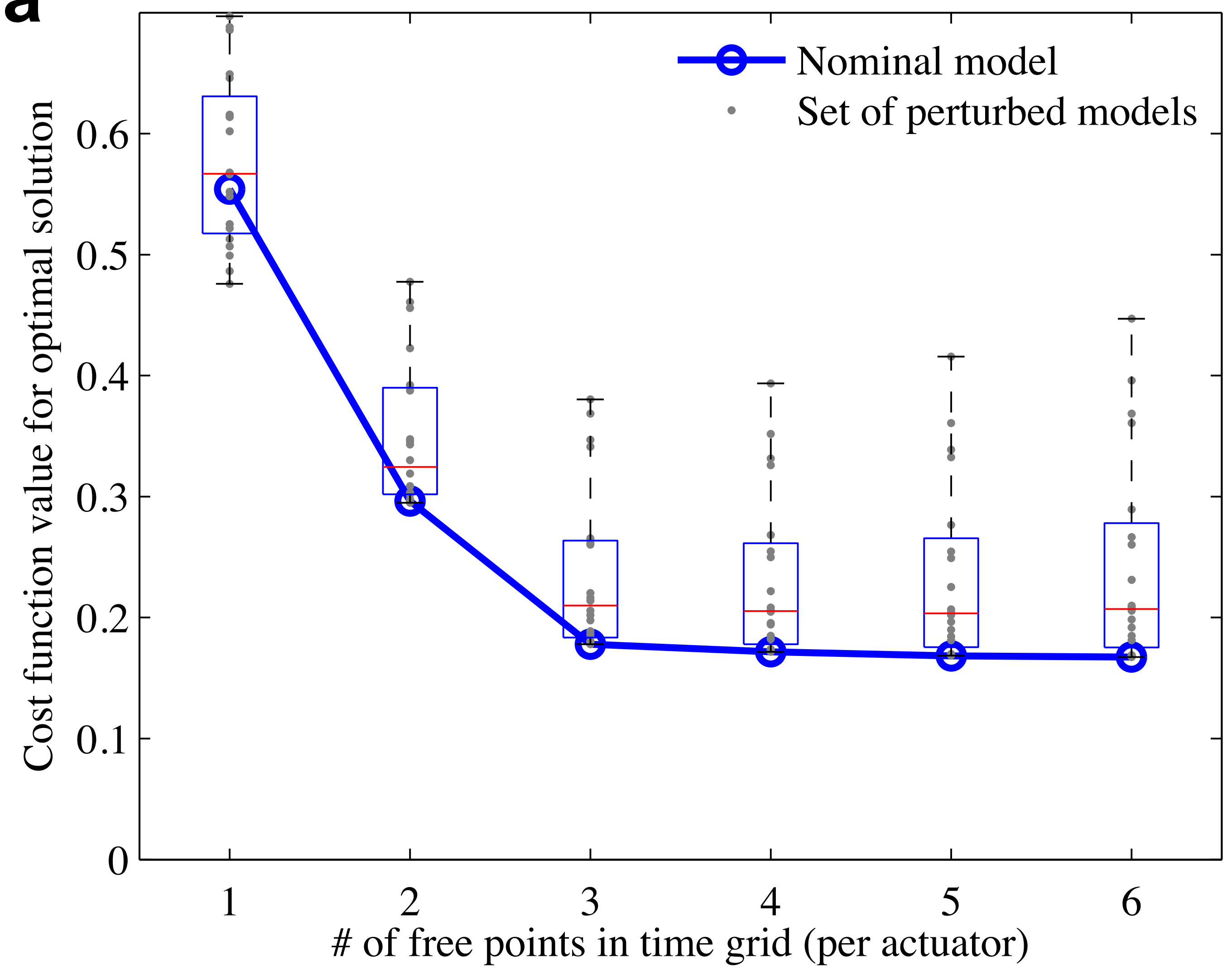
Multi-grid approach: validate solution against perturbred models to test generalization

- **Global nonlinear optimization problem: Risk of local minima**
- **Multigrid approach**
  - **Start with 1 free parameter, optimize**
  - **Increase number of parameters and start from last optimal solution**
- **Check generalization capabilities of solution by testing against set of perturbed models**
  - **Little improvement in nominal solution for $n_f>4$**
  - **Degradation in perturbed models for $n_f>3$**



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Different constraints are active at different times during the ramp-up, consequences for control

- **Similar scenario, only $U_{pl,edge}$>0 constraint**
- **Cost function gradient**
  - Move in this direction to decrease cost
- **Constraint gradient**
  - Move in this direction to violate constraint
- **Input arc classification**
  - Input constrained
  - State constrained
  - Unconstrained
- **Consequences for feedback control design**