Real-time model-based plasma state estimation, monitoring EX/P8-33 and integrated control in TCV, ASDEX-Upgrade and ITER









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Abstract

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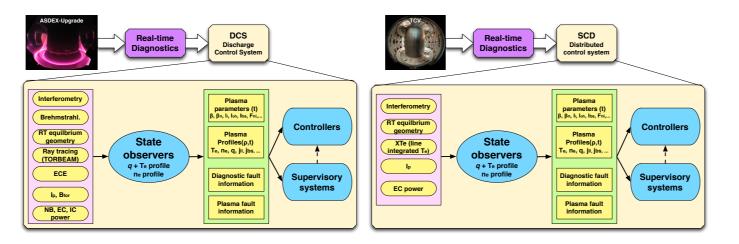
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We present recent progress in model-based approaches for plasma state estimation, monitoring and control and applications on TCV, AUG, RFX and ITER.

- State estimation: merge physics model predictions with realtime measurements yielding estimates of plasma state. Implemented at TCV, AUG and RFX.
- Integrated control: Model-based control algorithms, including Model Predictive Control, have been tested for control of TCV plasma density, temperature and current density profiles. Optimization-based algorithms were used to study optimal plasma ramp-up and ramp-down, as well as shot-to-shot scenario optimization. Applications to TCV, AUG and ITER.

3.2 Implementation on TCV and AUG with different RT diagnostics



3.3 Results: temperature and q profile reconstruction on AUG and RFX

5. Model-based plasma scenario monitoring: principles and first results

5.1 Approaches to disruption avoidance, prediction, mitigation

- Presently, most tokamaks employ disruption prediction and mitigation only as a 'last line of defense'.
- This approach is not advised for ITER and other large tokamaks, where use of disruption mitigation systems (DMS) should be minimized.
- Instead, advanced algorithms in the PCS should provide a 'first line of defense', avoiding disruptions when the plasma parame-

6.2 Iterative Learning Control

- Due to model-reality mismatch the optimized trajectories may not yield the correct result.
- Iterative Learning Control is a method to adapt the trajectories automatically from shot to shot to 'learn' the trajectories that yield the desired plasma evolution in the experiment.
- Method: Perform an experiment \rightarrow Compute error w.r.t. desired plasma evolution (offline) \rightarrow Solve optimization problem yielding modification of trajectories to decrease error. \rightarrow Repeat experiment.
- Application: Current density profile control in TCV experiments (left) and ITER simulations (right) [7]. ITER ramp-up density control with gas and pellet actuators (EX/P6-36).

• Monitoring: Real-time monitoring of plasma condition w.r.t. model-based expectation of plasma evolution can serve as a first line of defense to avoid reaching (disruption) limits. Prototype implementation shown for ASDEX-Upgrade.

All these approaches are based on physics-based, control-oriented models of the plasma evolution, which allow use of established tools from systems & control engineering community.

1. Introduction

- Control systems of future tokamaks will rely on advanced control functions to obtain high performance plasmas, with long duration and high repeatability. Some of these functions, also listed in [1] are shown in Figure 1
- Model-based design of the various algorithms minimize development time and allows extensive simulations for (formal) validation of the PCS components.
- Several new developments are shown that have been implemented on the TCV, AUG, RFX tokamaks, and simulations for ITED

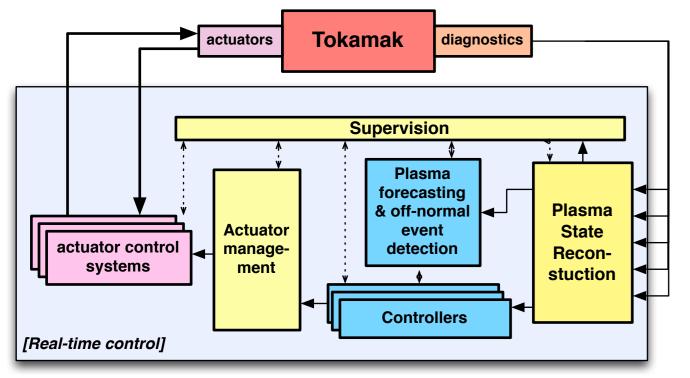
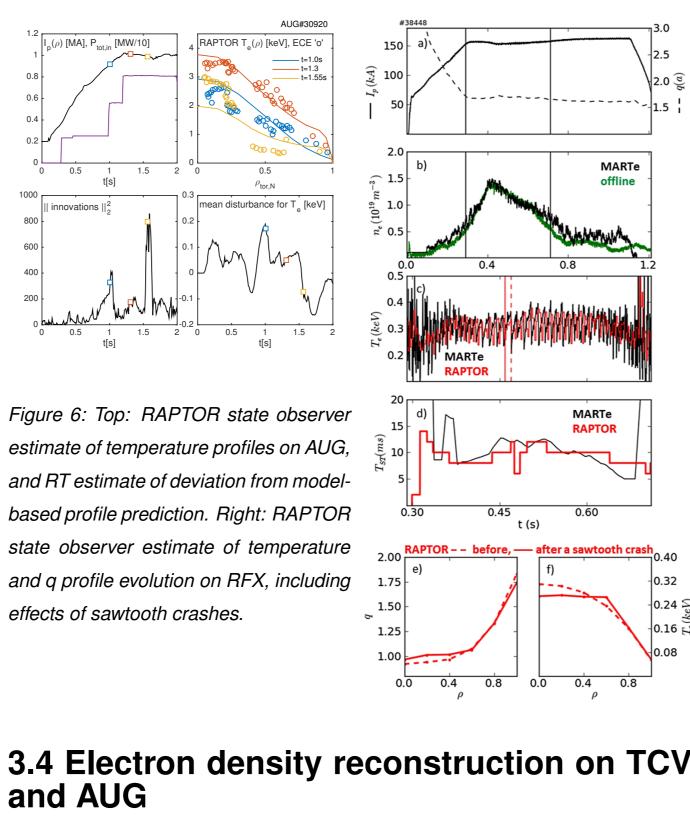
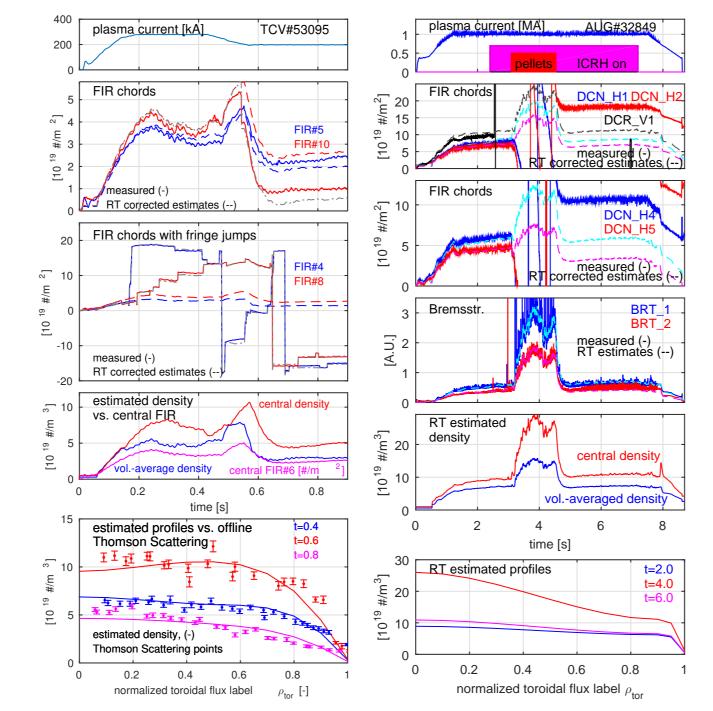


Figure 1: PCS scheme with advanced functions







ters leave a 'trusted zone' in the operating space. This is a combination of scenario monitoring, disruption prediction, avoidance and mitigation.

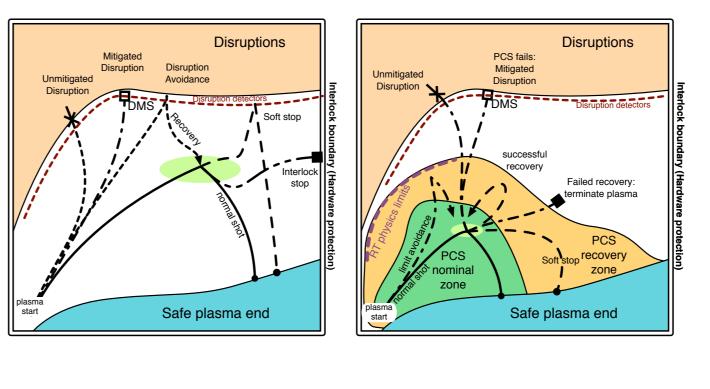
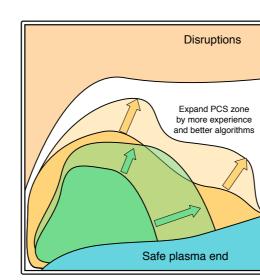


Figure 12: Illustration of present ap-Figure 13: Illustration of integrated approaches to disruption avoidance. proach for scenario monitoring.

This approach requires:



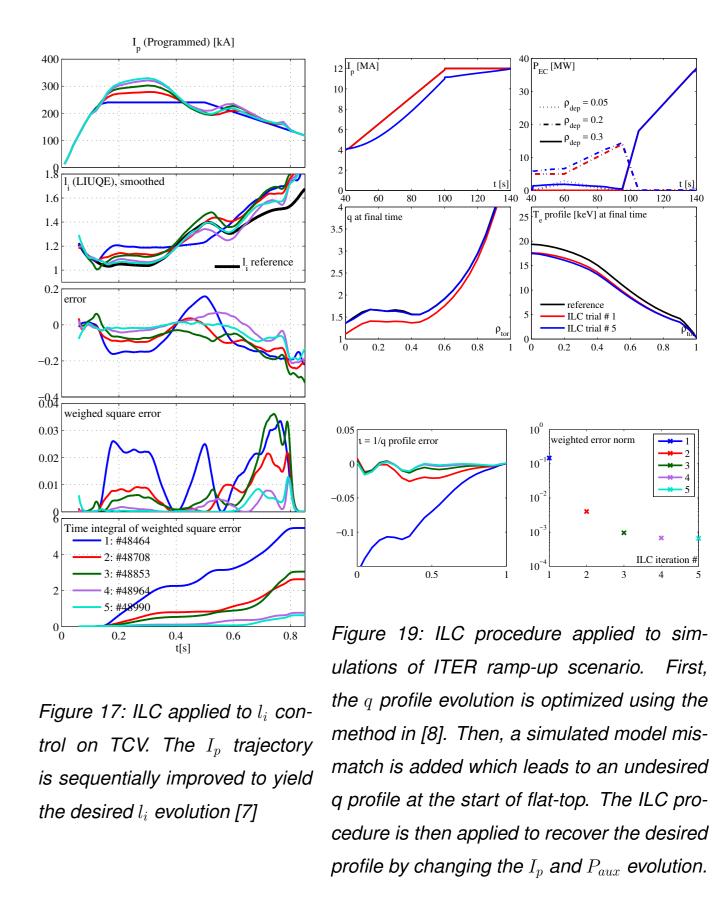
(state observers). • Real-time control of the plasma state to remain in the desired envelope. • Real-time monitoring of the estimated plasma evolution with respect to the (real-time) predicted evolution. • Real-time monitoring of plasma state with respect to known disruption limits.

• Real-time estimate of the plasma

state based on multiple diagnostics

5.2 Prototype implementation of real-time monitoring on AUG

- Monitoring plasma evolution w.r.t. model-based expectation: first tests during EUROfusion MST1 campaign 2016.
- AUG control system runs two versions of RAPTOR:
- RAPTOR-observer: estimate of plasma temperature profile



6.3 Optimization-based actuator allocation algorithm

- Actuator allocation: decide which actuator will be used for what control task. in real-time.
- Formulated in [9] as nonlinear optimization problem (brute force computation).
- We propose a reformulation as a Mixed Integer Quadratic Programming problem, solvable in <<1s on ordinary CPU even for ITER-scale problem.

2. Control-oriented models of plasma core profile evolution

2.1 RAPTOR real-time plasma profile simulator

- RAPTOR [2] [3] solves core $\psi(\rho, t)$ and $T_e(\rho, t)$ evolution equations including main nonlinear couplings.
- Source and transport models parametrized. Time-varying equilibrium geometry externally specified.
- Real-time capable on present tokamaks (1ms per time step), faster than real-time for ITER.

2.2 Particle transport model

- 1D plasma density profile model including vessel and wall particle inventory. [4]
- transport coefficients, parametrized particle – Empirical sources.

2.3 RAPTOR simulation of AUG discharge

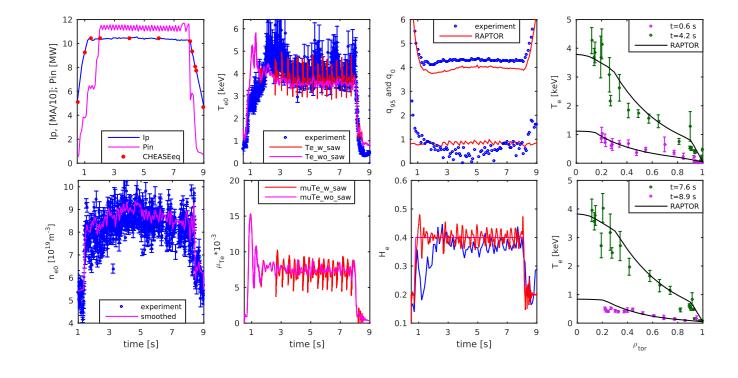


Figure 2: RAPTOR simulation of H-mode AUG discharge using the gradient-based electron heat diffusivity transport model. The equilibrium geometry, particle density, H factor and plasma current evolution are prescribed, and the simulation correctly reproduces temperature profiles and simulates q profile evolution including sawteeth. μ_{T_e} represents the scaling of the pedestal to achieve the prescribed H factor.

Figure 8: Reconstruction of TCV Figure 9: Reconstruction of AUG plasma particle density using a dy-plasma particle density using a state namic state observer in the presence observer in the presence of ICRH of fringe jumps on interferometer chan- and pellets which render interferometer nels. measurements invalid.

4. Model-based control

4.1 Simultaneous control of plasma β , n_e and q profile on TCV

- Model-based approach: use models to design controllers, and for closed-loop testing before application to experiment.
- Result controllers usually work on first trial and require minimal or no manual tuning on the system itself.
- TCV experimental results (MST1 campaign 2016) used two EC sources (P_A , ctr-ECCD) and P_B (co-ECCD)) for heating and current drive. Demonstrated combined operation of:
- Model-based state observers for plasma particle density, temperature profile and q profile (RAPTOR).
- Robust controller for plasma density using gas valve [5].
- Model Predictive Controller (MPC) for plasma β and q profile,

- merging model + measurements.
- RAPTOR-predictive: model-only prediction of temperature evolution.

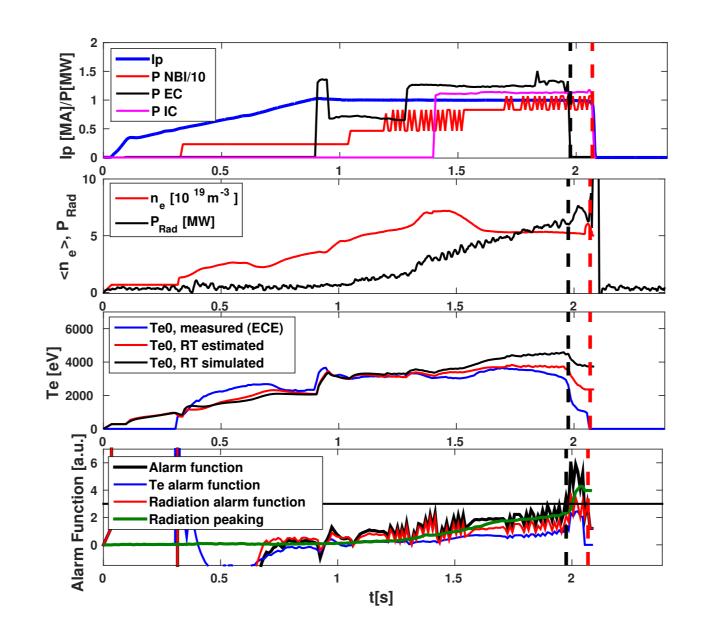
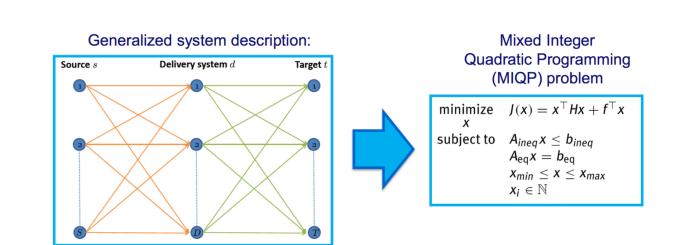


Figure 15: Example of model-based plasma monitoring on ASDEX-Upgrade. Due to impurity accumulation, the plasma radiates more than expected, resulting in a discrepancy between the real-time predicted, reconstructed, and ECE measured temperature. This information can be used in the future as signal to a supervisory control system.

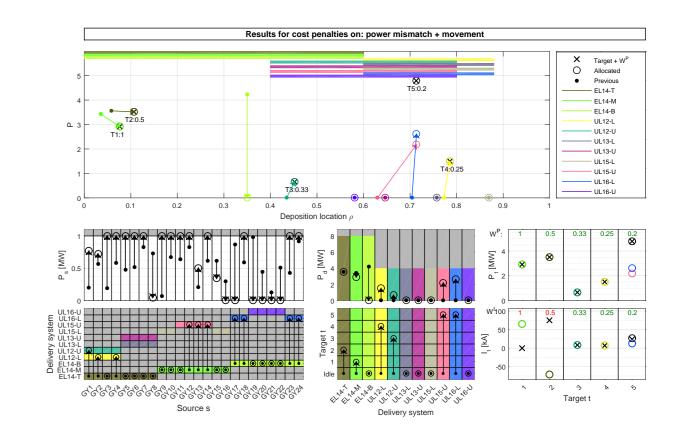
6. Numerical optimization for plasma control

6.1 Actuator trajectory optimization

- Tokamak plasma evolves in response to actuators (auxiliary power, coil currents...).
- Goal of tokamak operations: achieve desired plasma state evo-



• Application to ITER: optimize allocation of 24 gyrotrons to various targets with different ρ_{dep} , $P_{request}$, $I_{cd,request}$, while minimizing change w.r.t. previous allocation.



7. Outlook

- Improve models: add transport equations for multiple species, pedestal parametrization, neural network emulations of quasilinear gyrokinetic fluxes [10]
- Develop and test tools for model-based disruption limit avoidance and plasma supervision algorithms.
- Continue deploying model-based control, reconstruction, and monitoring on TCV, AUG, RFX and other tokamaks, aim for routine use of these tools in discharge development and operations

3. Real-time state reconstruction on **ASDEX-Upgrade**, **TCV** and **RFX-mod**

3.1 Dynamic state observer

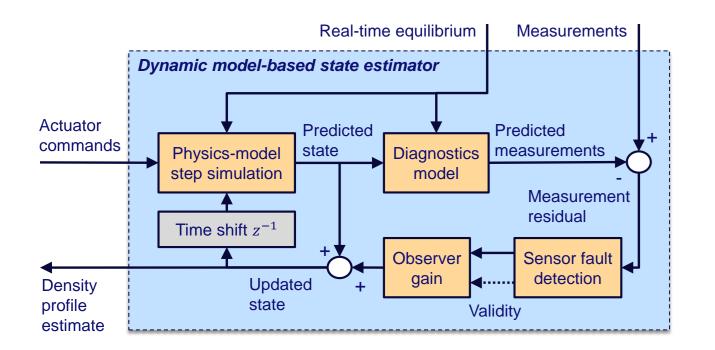


Figure 3: Plasma state reconstruction using a dynamic state observer: merge diagnostic measurements and model predictions. Real-time checks of measurement residuals allow detection of faults in diagnostics and/or plasma. **26th IAEA Fusion Energy Conference**, Kyoto, Japan, – 17-22 October 2016 - EX/P8-33

- predicts plasma evolution and takes (time-varying) constraints into account [6].
- Isoflux-based plasma shape controller (see EX/P8-32)

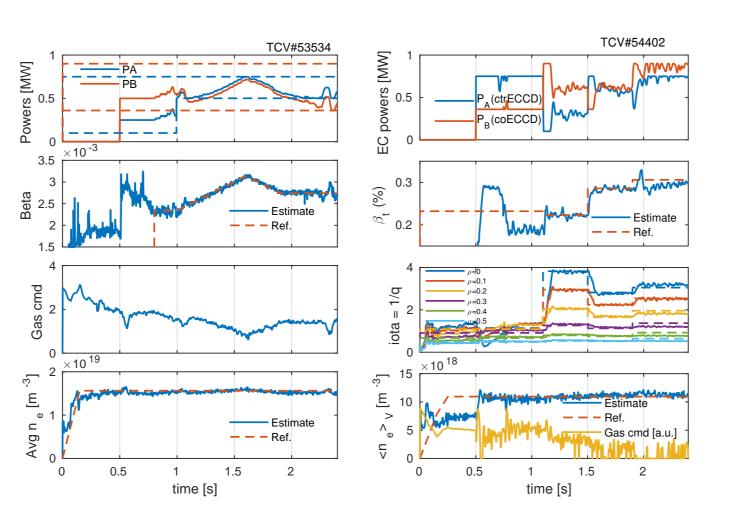


Figure 10: Simultaneous control of Figure 11: Simultaneous control of plasma density and beta using model- plasma density, and model-predictive based controllers on TCV. Two EC control (MPC) of β and $\iota = 1/q$ on TCV. sources (P_A/P_B) are used for heat- q evolution model did not include sawing. Model-predictive controller (MPC) teeth, therefore the state observer finds is used for β control q < 1.

- lution.
- Approach: formulate as an optimization problem.
- In practice: Nonlinear constrained optimization problem, solve using Sequential Quadratic Programming.
- Example: Ramp-down trajectory optimization for AUG
- Compute evolution of $I_p(t)$, $\kappa(t)$, $P_{aux}(t)$ for fastest possible plasma ramp-down that avoids known physics constraints.

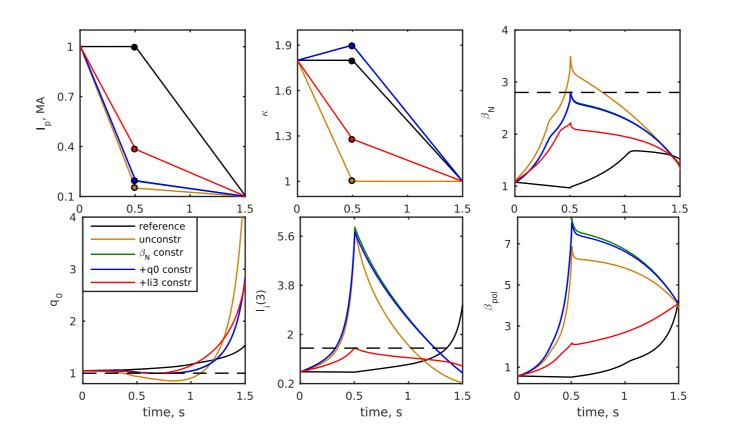


Figure 16: Example of ramp-down optimization for an AUG-like plasma. Constraints on β_N , q_0 and l_{i3} are successively added, leading to different timetrajectories for plasma current and elongation.

8. Acknowledgements

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