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Development of Data Assimilation System for Control of Toroidal Plasmas

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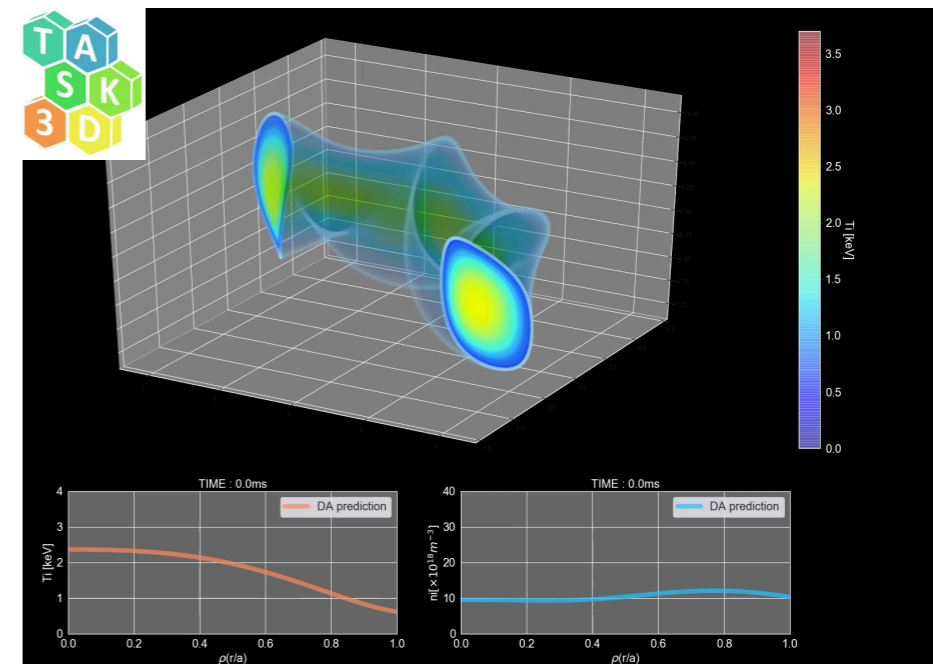
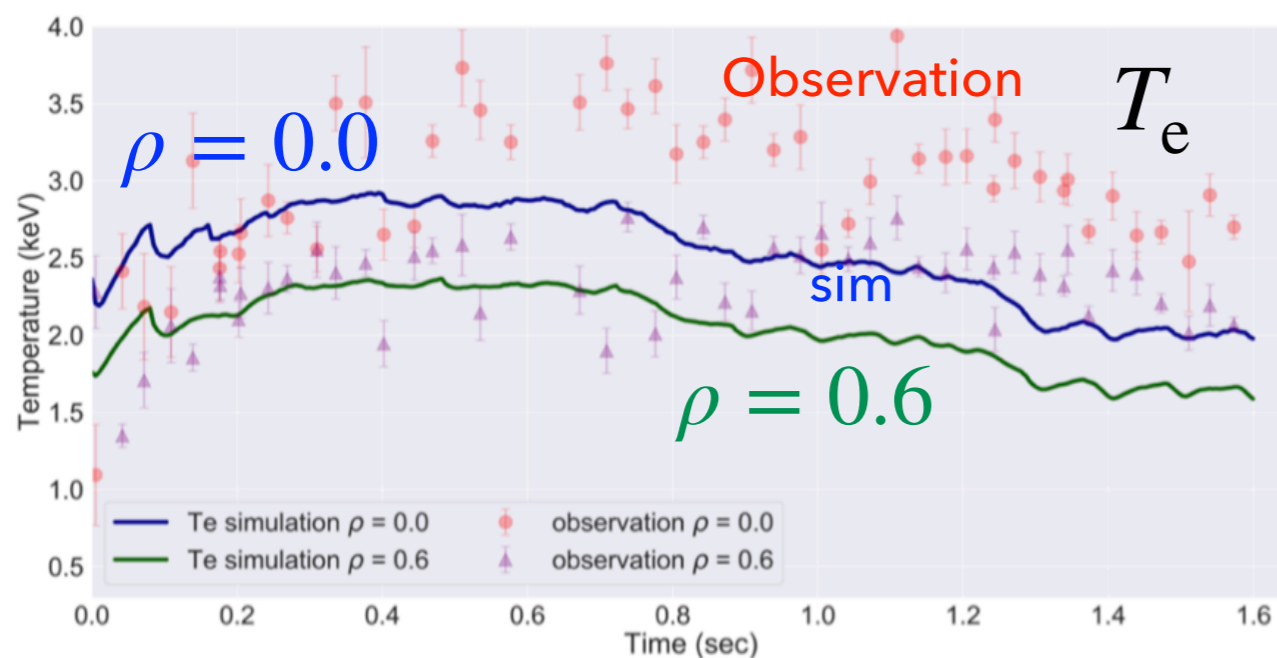
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Introduction

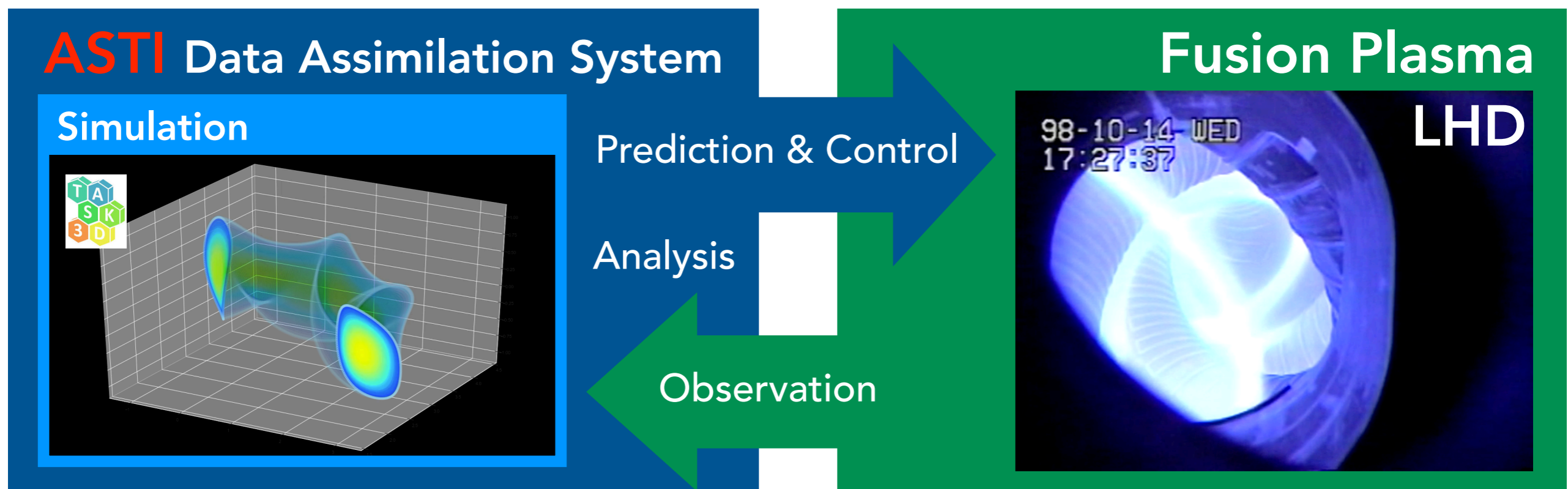
- ▶ Fusion plasma is a complex system containing various spatiotemporal scale physical phenomena. Several integrated simulation codes have been developed to predict and analyze the behavior of the entire fusion plasma.
- ▶ The integrated simulations have various uncertainties in each of the employed models, and the interaction of them makes the entire simulation results highly uncertain. In addition, uncertainties not included in the model, such as wall condition, may affect the plasma performance.
- ▶ It is difficult to achieve fast and accurate prediction with the present integrated simulation codes.

To overcome these problems, we introduce the **data assimilation** techniques.



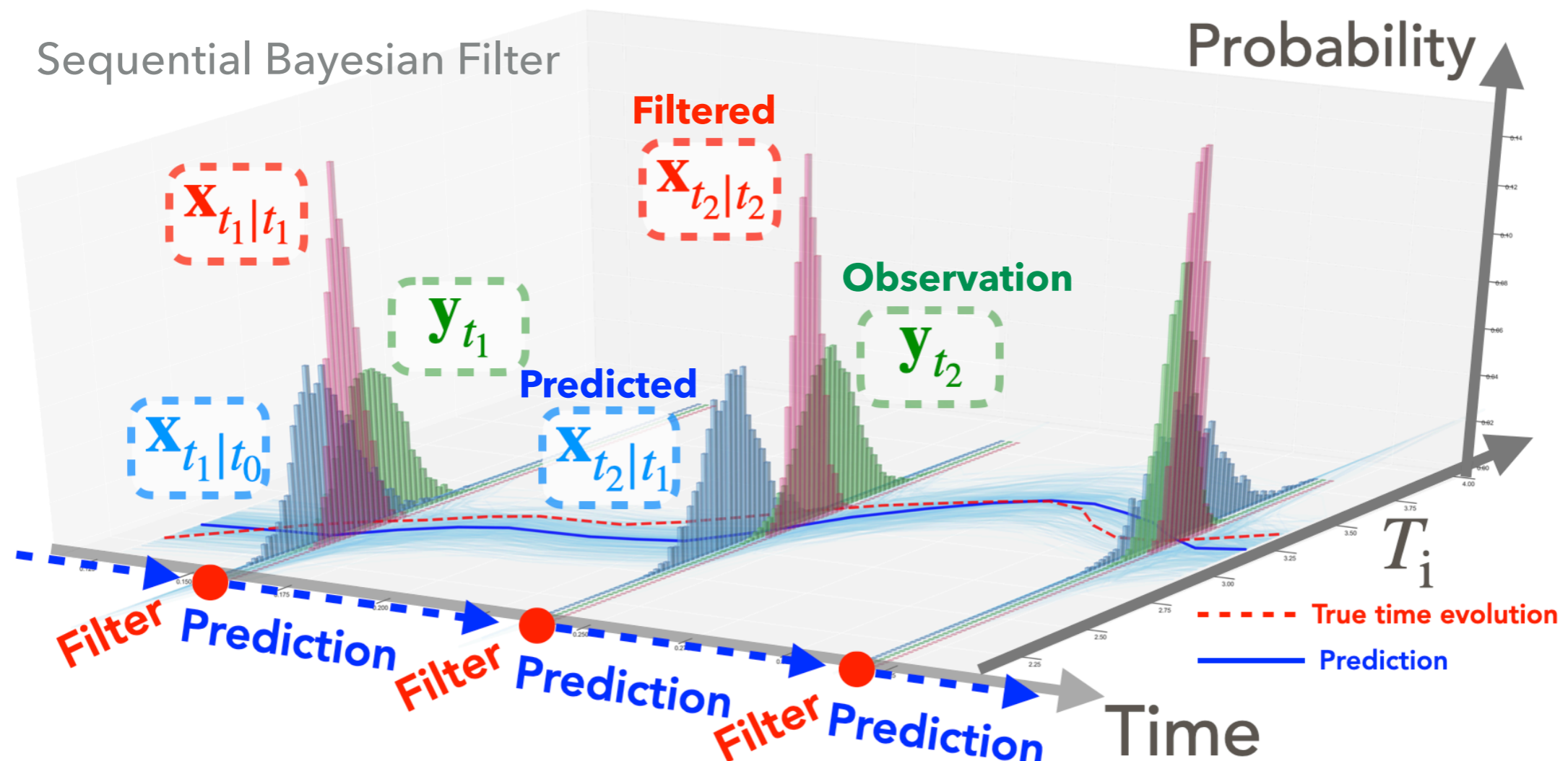
Data Assimilation System

- ▶ To realize a numerical system that can predict and control the behavior of fusion plasmas with high accuracy, we are developing a data assimilation system, **ASTI**.
- ▶ Data assimilation is a statistical estimation methods. It optimizes the state vector to enhance the prediction capability and reproducibility of the employed simulation model based on the observation data.
- ▶ In ASTI, we employ the ensemble Kalman filter (EnKF) and the ensemble Kalman smoother (EnKS) as the data assimilation techniques.

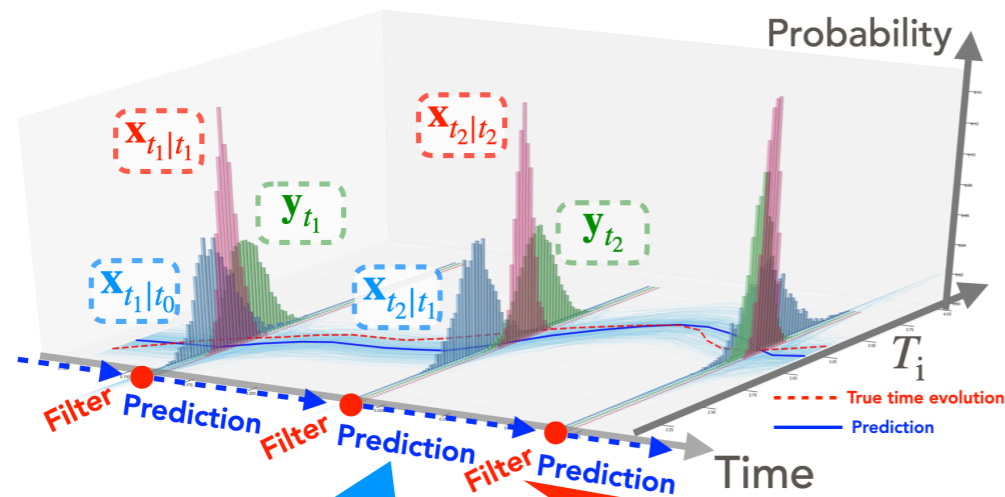


Data Assimilation

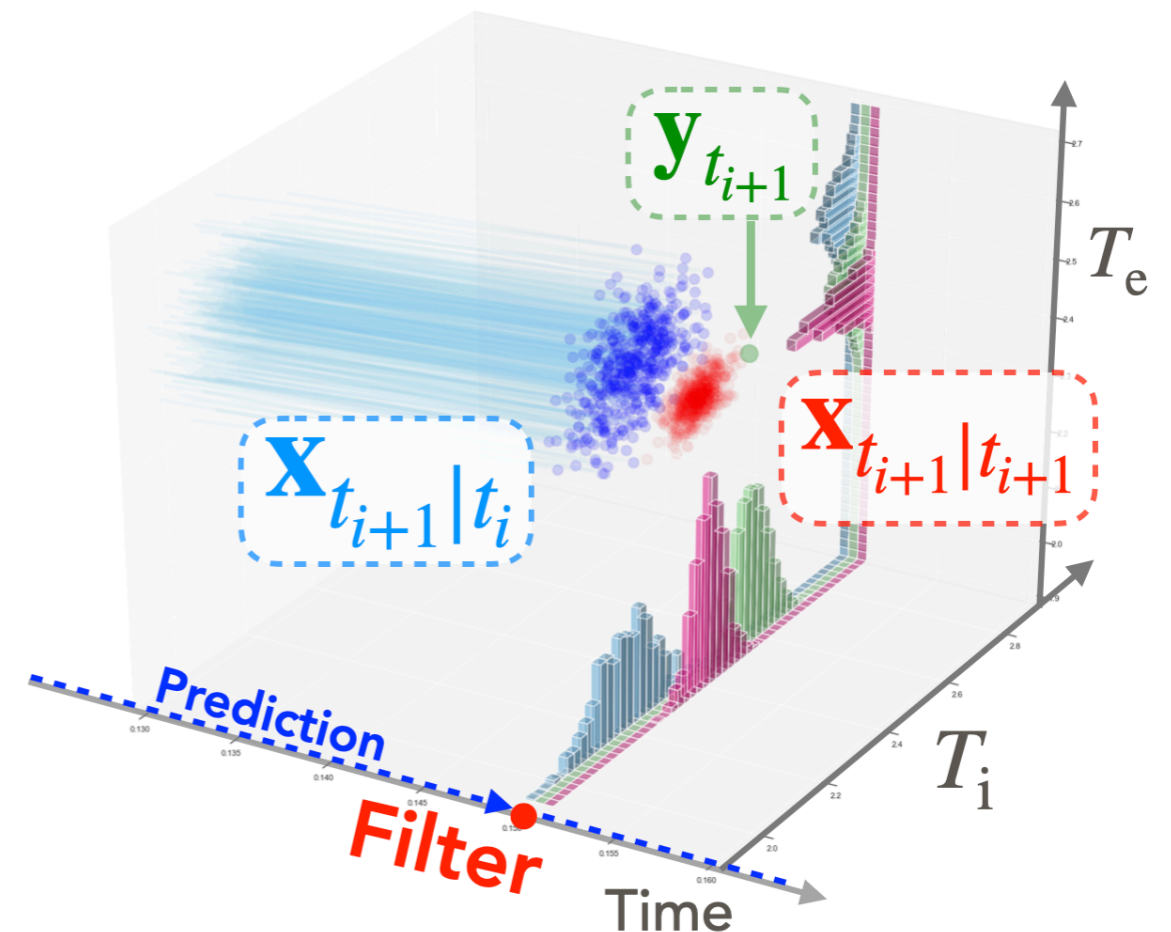
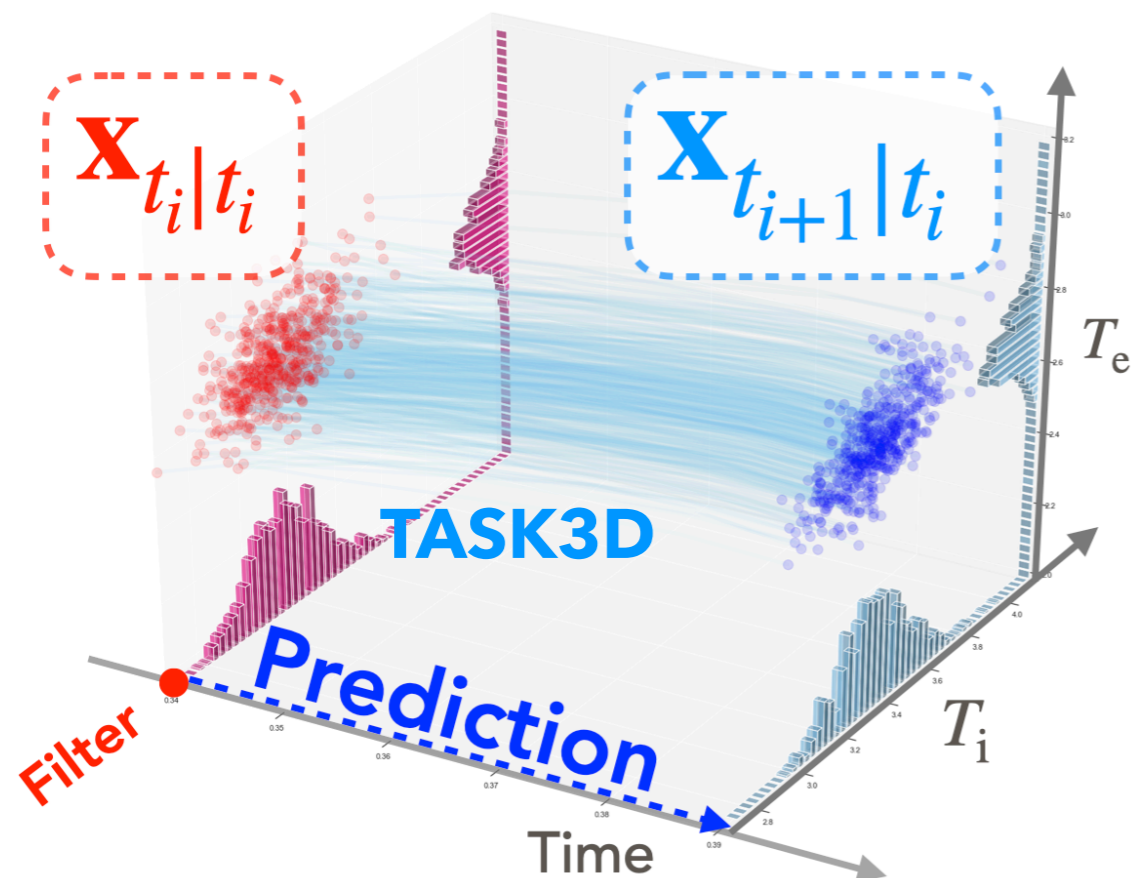
- ▶ The procedure of data assimilation (**Sequential Bayesian Filter**) is a loop of prediction and filtering.
- ▶ The filter optimizes the state vector to enhance the prediction capability of the simulation model based on the observation data.
- ▶ Data Assimilation can also be used to estimate the variables that can not be observed and the model parameters that can explain observation data.



Ensemble Kalman Filter (EnKF)



- ▶ **EnKF** assumes a **nonlinear system model** and the **Gaussian distribution** as the probability distribution.
- ▶ The probability distribution of state vector is approximated by an ensemble.

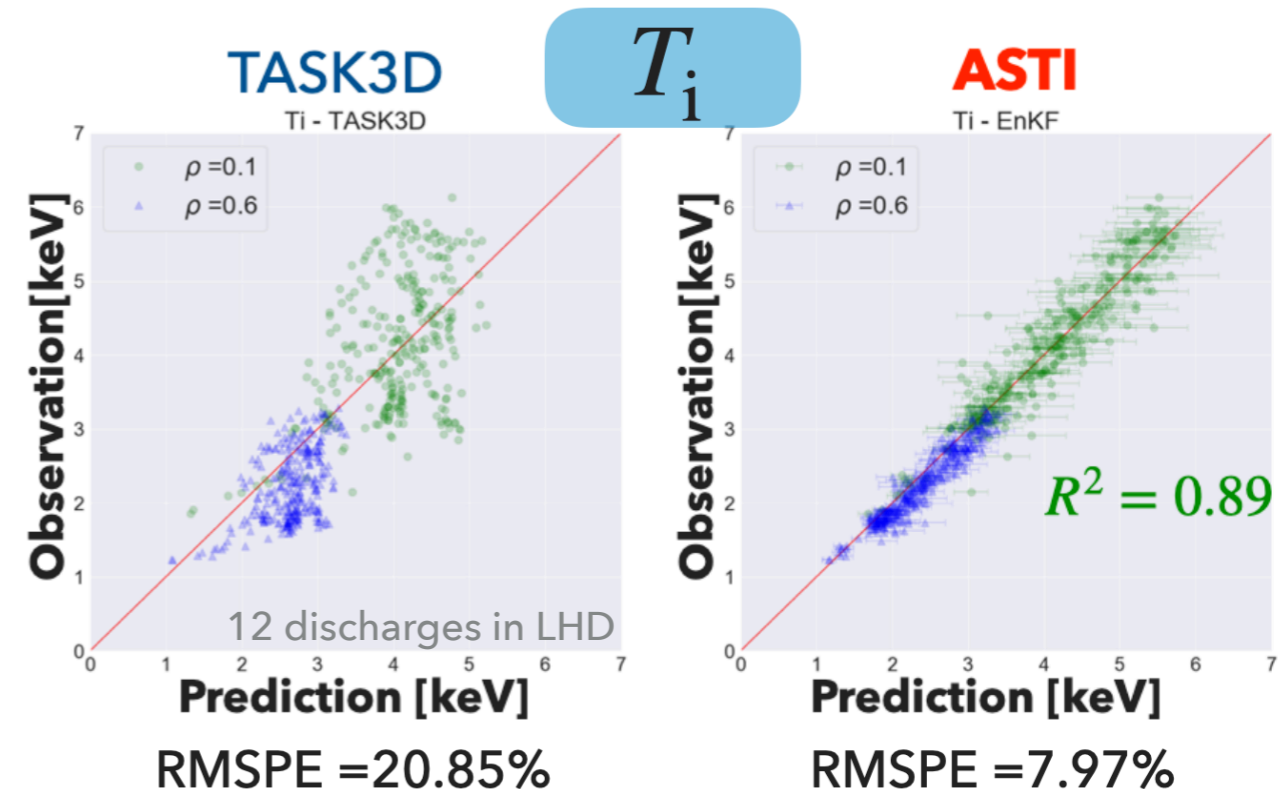
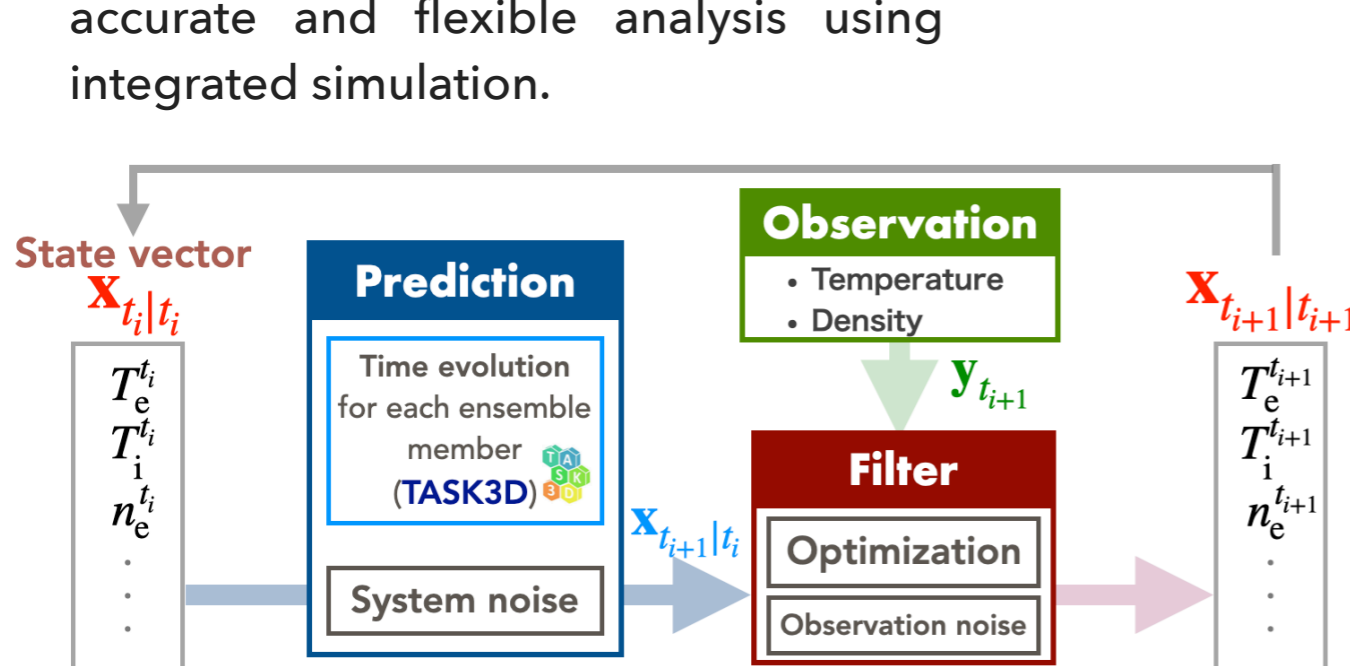
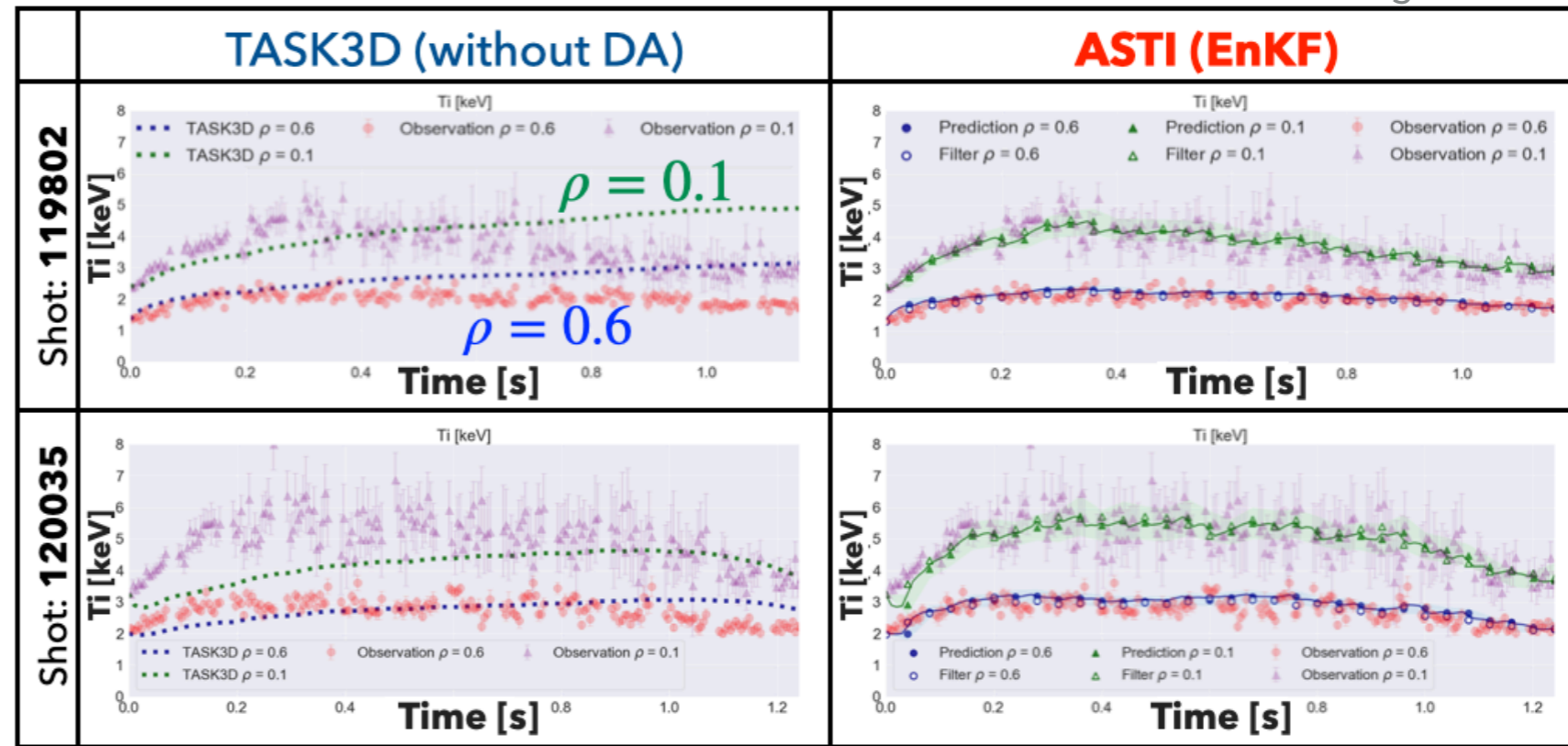


Data Assimilation System ASTI

- We are developing **ASTI** based on the integrated simulation code, **TASK3D** to predict and control the behavior of fusion plasmas.
- We have applied ASTI to several experimental time series data sets of NBI heated discharges in LHD. ASTI has reproduced the observation time series data with high accuracy and estimated the model parameters (e.g., turbulent diffusivities).
- Data assimilation allows for highly accurate and flexible analysis using integrated simulation.

Ion temperature

NBI-heated discharges in LHD

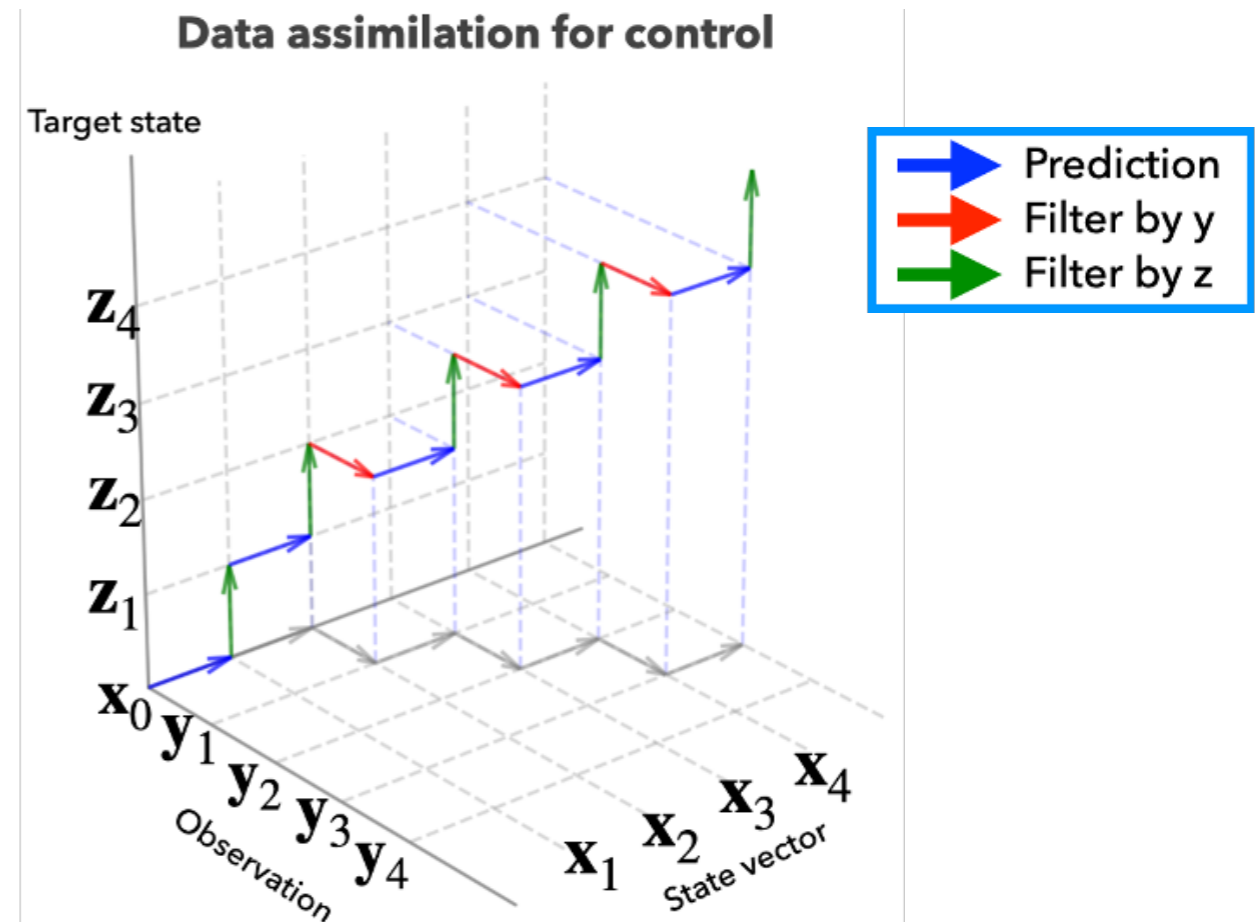
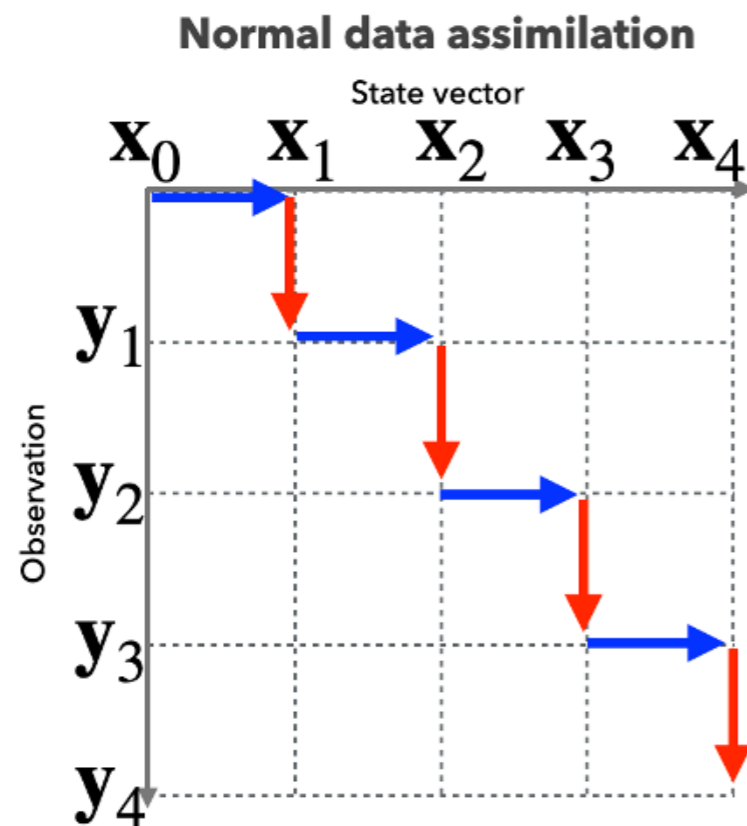
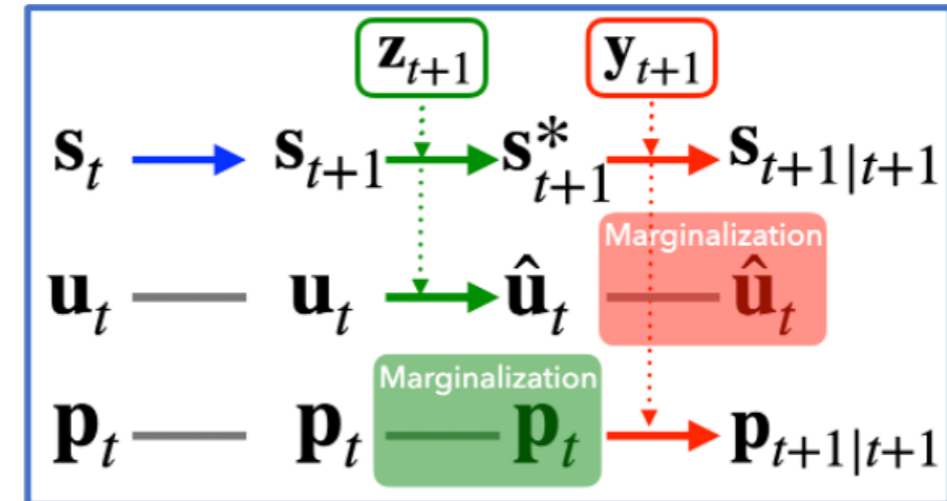


Extension to a control system

- The state vector consists of three parts.

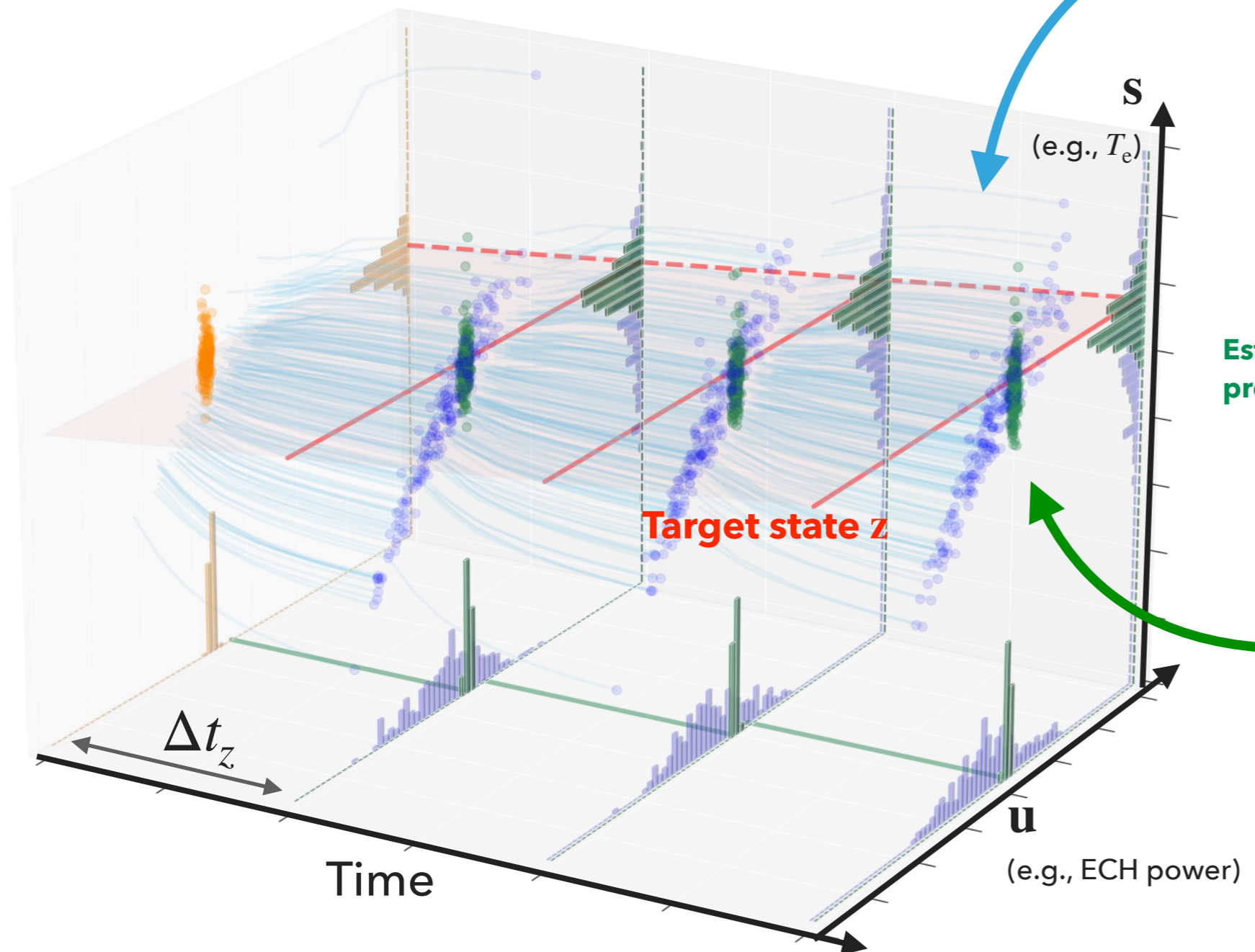
$$\mathbf{x}_t = \begin{pmatrix} \mathbf{s}_t \\ \mathbf{u}_t \\ \mathbf{p}_t \end{pmatrix} \begin{array}{l} \mathbf{s}_t: \text{State of the system} \\ \mathbf{u}_t: \text{Control input from } t \text{ to } t+1 \\ \mathbf{p}_t: \text{Model parameter} \end{array}$$

- The state \mathbf{s} and model parameter \mathbf{p} are optimized by assimilating observations \mathbf{y} (Normal data assimilation).
- In addition, This method also estimates the optimal control input $\hat{\mathbf{u}}$ which are likely to achieve the target state \mathbf{z} .

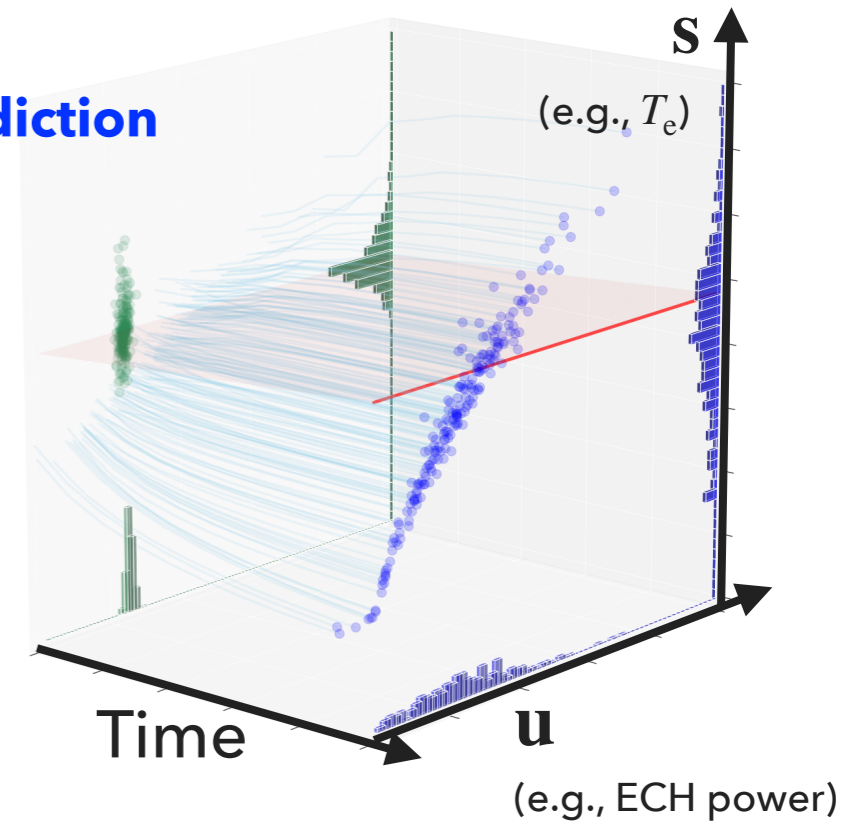


Filter for control Element of the control algorithm ①

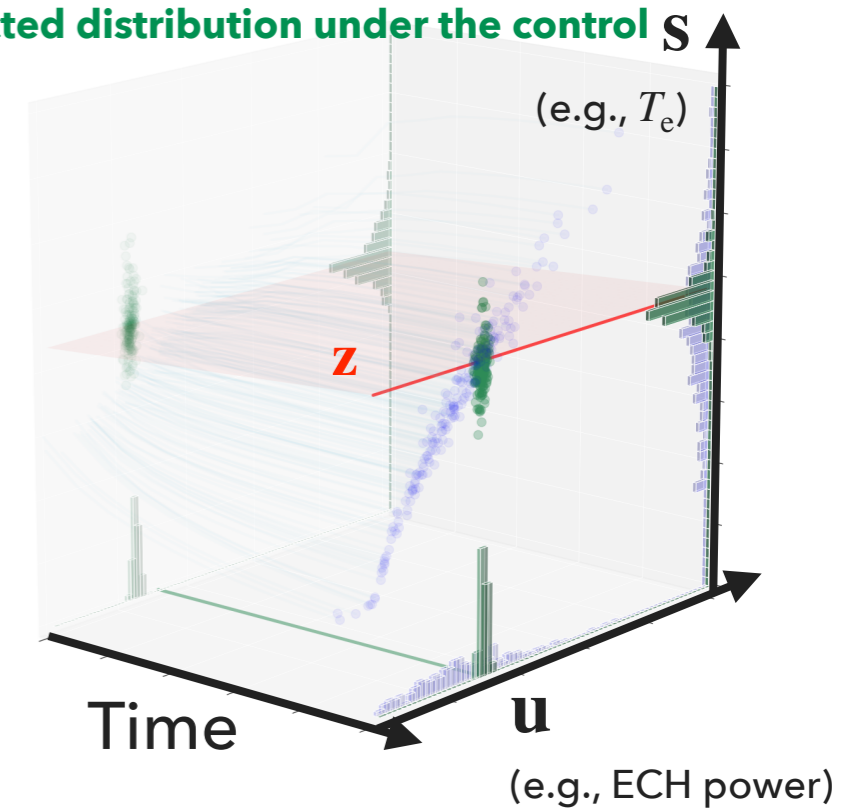
This filter estimates the control input which is likely to achieve the target state \mathbf{z} and computes the predicted distribution under the control. This filter is composed of two filters (one to assimilate \mathbf{z} and one to assimilate \mathbf{u}). This filter is assumed to be executed at Δt_z intervals.



Prediction



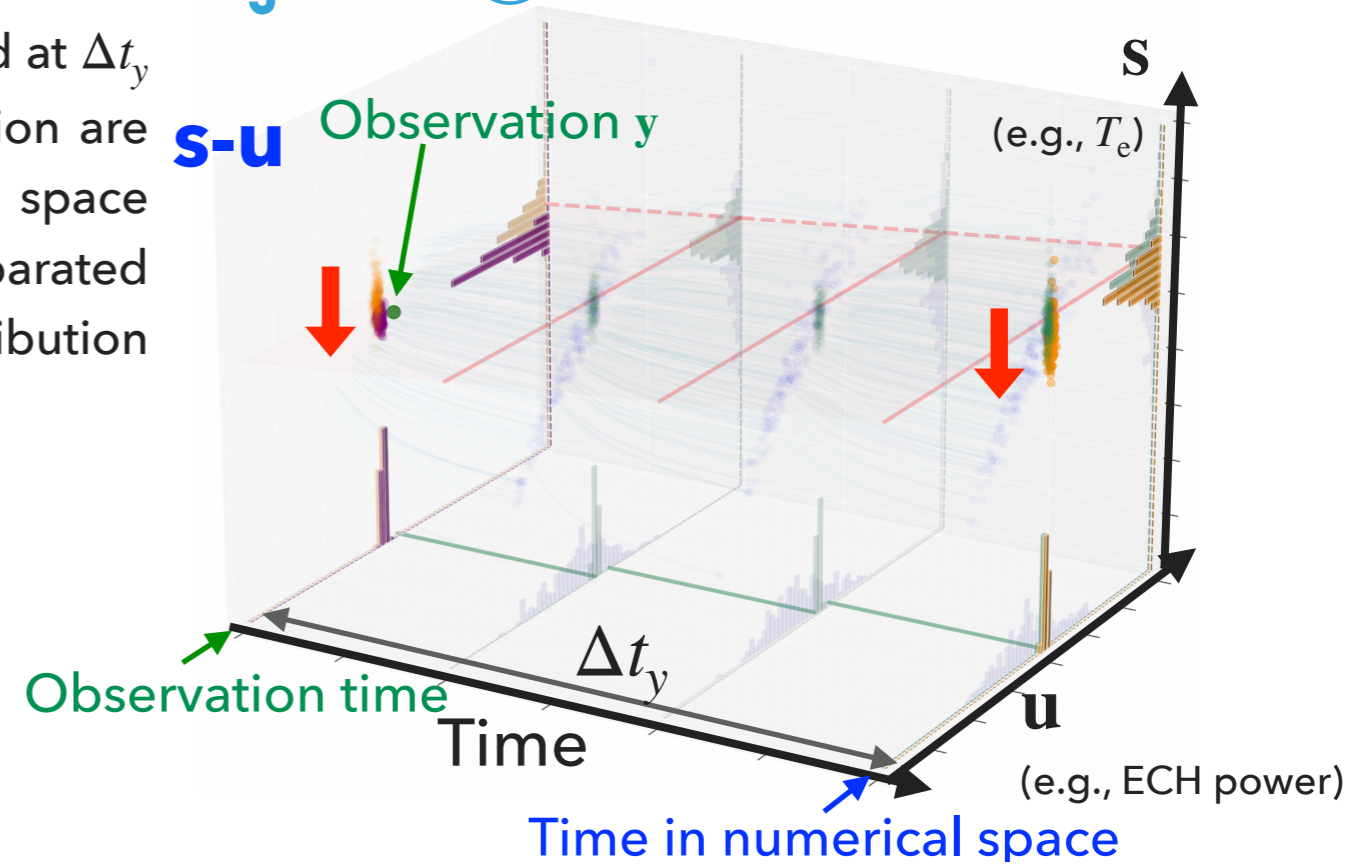
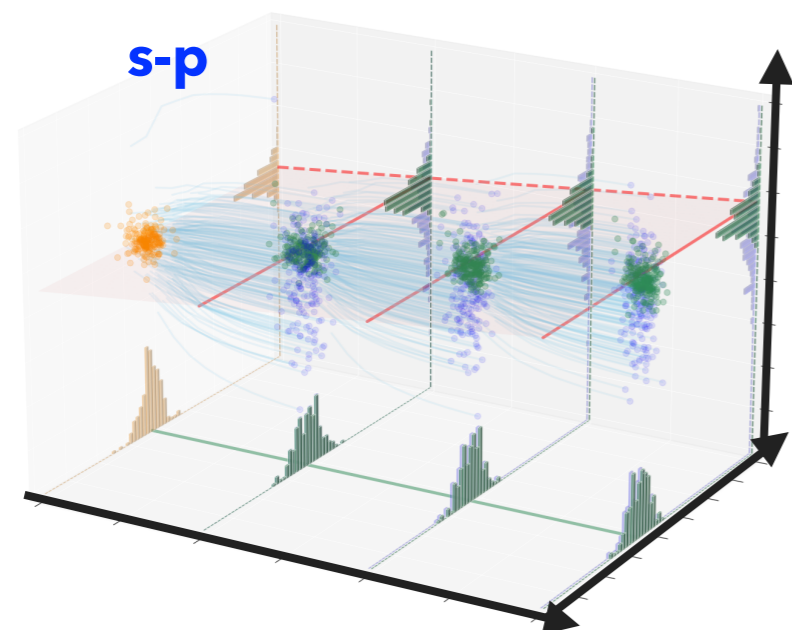
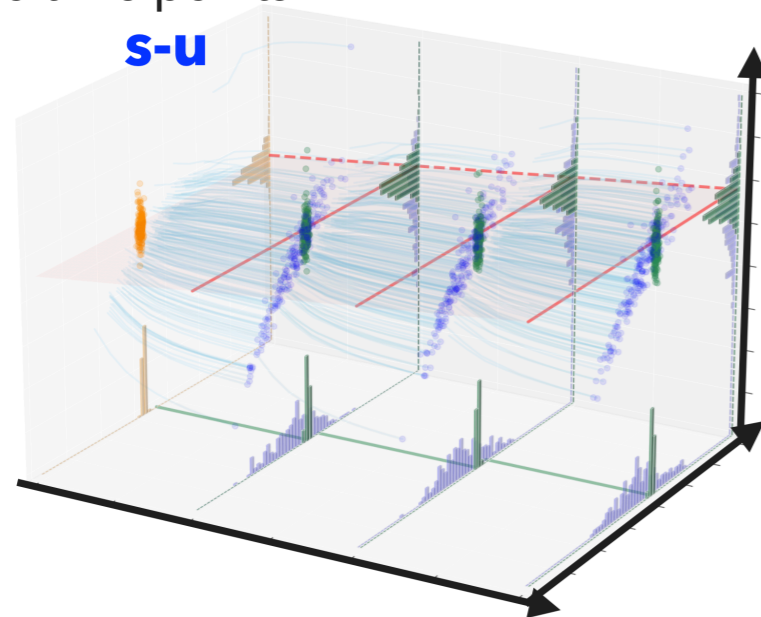
Estimating an optimal control input and the predicted distribution under the control \mathbf{S}



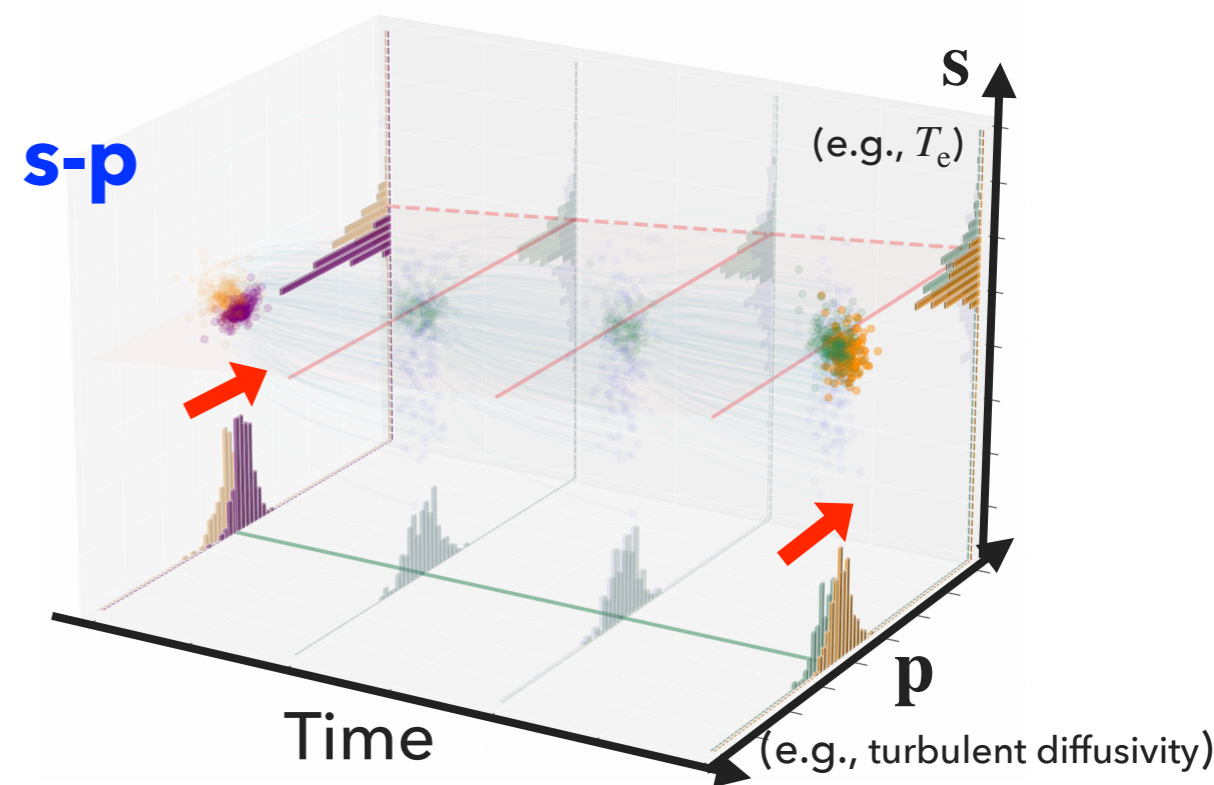
Filter for observation

Element of the control algorithm ②

We consider a situation where the observations are obtained at Δt_y intervals ($\Delta t_y = 3\Delta t_z$). Since the time at which the observation are obtained and the time of the latest prediction in numerical space differ by Δt_y , it is required to assimilate the observations separated in time. This can be achieved by considering the joint distribution of the two time points



The observation information is reflected in the latest predicted distribution.



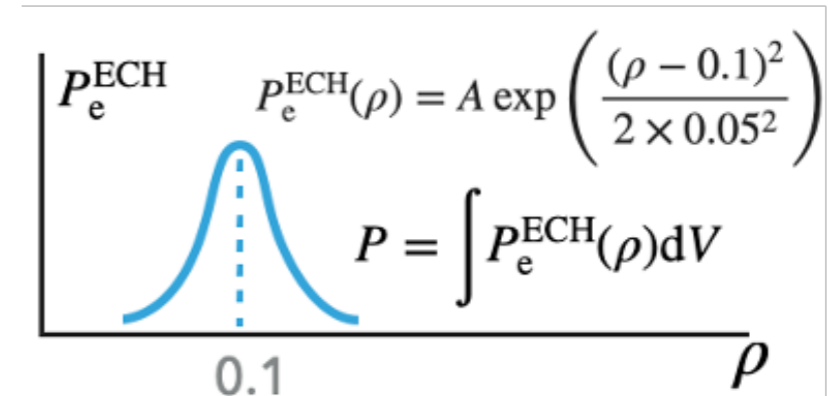
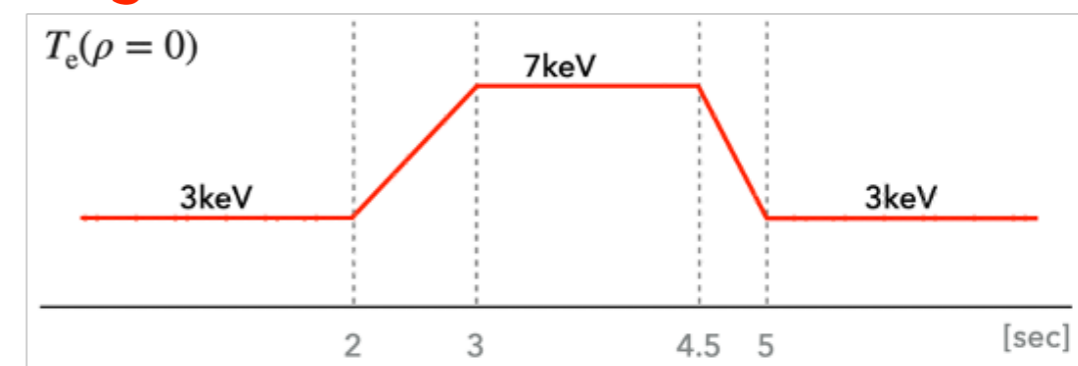
Numerical experiments



- ▶ We have implemented this control algorithm in ASTI and investigated the control performance by controlling the simulated virtual plasmas (TASK3D).
- ▶ We take T_e at the plasma center ($\rho = 0$) as the target state \mathbf{z} and assume that the radial profiles of T_e and T_i can be observed in the cycle of $\Delta t_y = 0.5$ s.
- ▶ The ECH input power is adjusted by ATSI in the range 0.5 - 5 MW in 0.5 MW increments ($\Delta t_z = 0.1$ s).
- ▶ This performance tests are performed by 400 ensemble members. The electron density at the plasma center is assumed to be $1.0 \times 10^{19} \text{ m}^{-3}$.

State variable		Dimension	Standard deviation of system noise	
Te	Electron temperature	s	7	3%
Ti	Ion temperature	s	7	3%
P	ECH input power	u	1	0.7MW
Ce	Factor for the electron thermal turbulent diffusivity	p	7	0.2
Ci	Factor for the ion thermal turbulent diffusivity	p	7	0.2

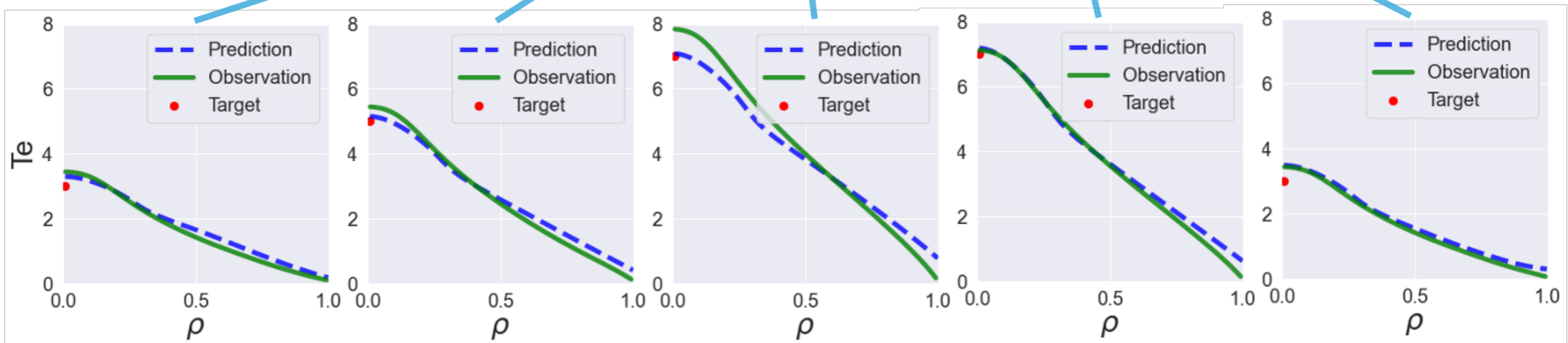
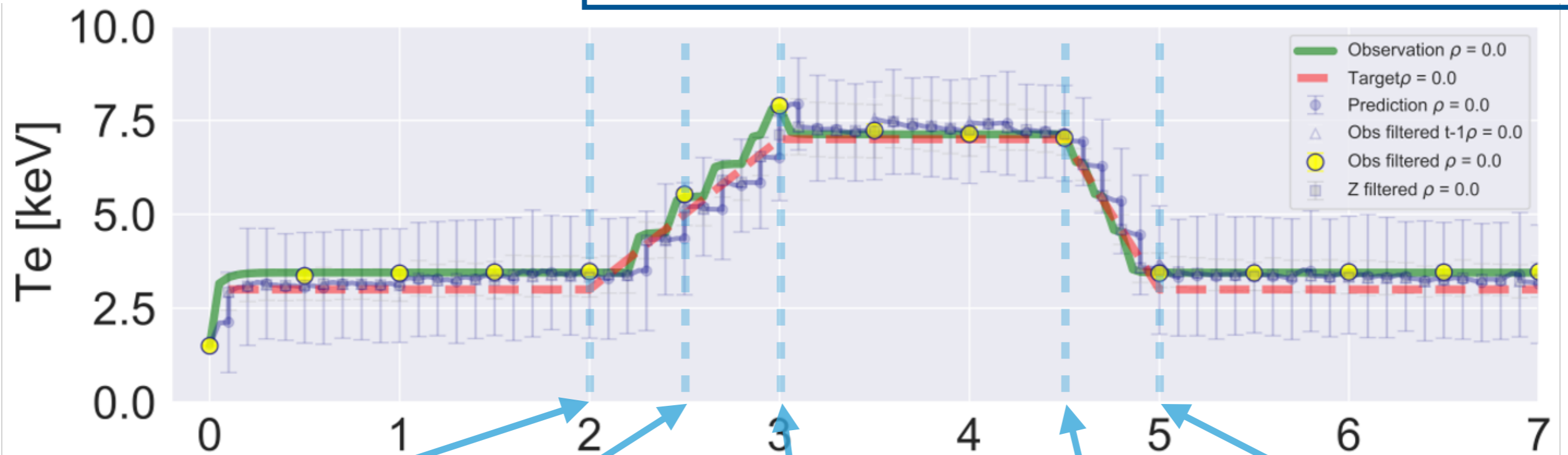
Target state



Simulation results

Electron thermal turbulent diffusivity

- Employed model in ASTI : $\chi_e^{TB} = C_{gB} \frac{T_e \rho_i}{eB a} \times C_e$
- Simulated plasma (TASK3D) : $\chi_e^{TB} = \frac{1}{2} \left(C_{gB} \frac{T_e \rho_i}{eB a} + C_{Alc} \frac{1}{n_e} \right)$

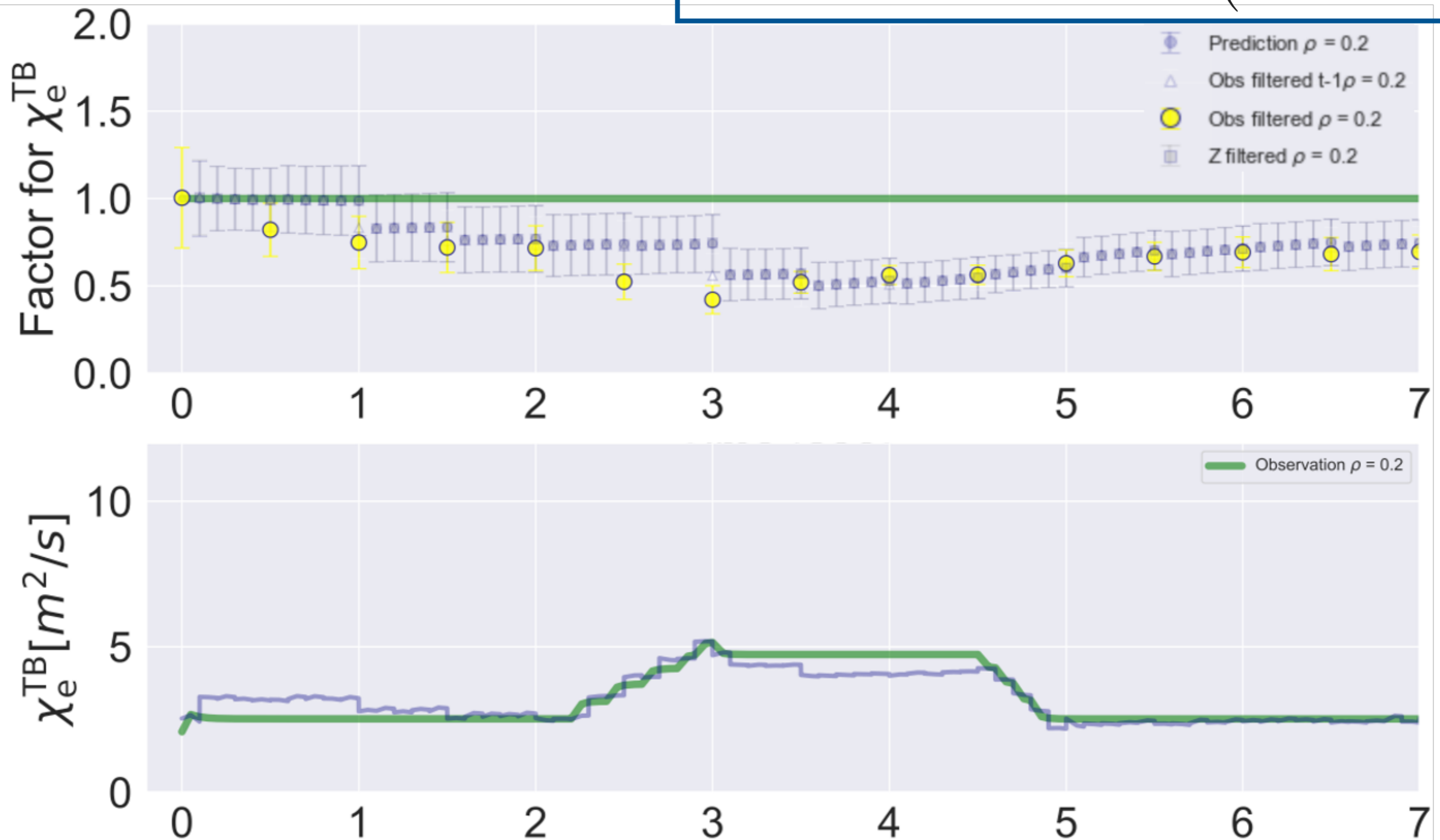


Simulation results

- Optimization of model parameter

Electron thermal turbulent diffusivity

- Employed model in ASTI : $\chi_e^{\text{TB}} = C_{\text{gB}} \frac{T_e}{eB} \frac{\rho_i}{a} \times C_e$
- Simulated plasma (TASK3D) : $\chi_e^{\text{TB}} = \frac{1}{2} \left(C_{\text{gB}} \frac{T_e}{eB} \frac{\rho_i}{a} + C_{\text{Alc}} \frac{1}{n_e} \right)$



Summary

- ▶ We have developed the data assimilation system, **ASTI**, to predict and control the behavior of fusion plasmas in real time.
- ▶ We have applied ASTI to the particle and heat transport simulation of LHD plasmas. The obtained density and temperature radial profiles and temporal variations have been agreed well with measured ones.
- ▶ We have investigated the **control method** of fusion plasma extending ASTI and have demonstrated the control of virtual LHD plasma (TASK3D).
- ▶ ASTI is expected to be a **robust system** for analysis, prediction, and control of fusion plasma that connects an actual plasma and a plasma in numerical space.
- ▶ We will start to apply ASTI controlling real LHD plasma and hope to control other device plasmas (JT-60SA, ITER, ...).