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Improved Prediction Scheme for Turbulent Transport by Combining Machine Learning and First-Principle Simulation

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Abstract

A novel scheme to predict the plasma turbulent transport is developed by combining the mathematical optimization techniques employed in the machine learning and the first-principle gyrokinetic simulations. The gyrokinetic simulation as a first-principle approach is powerful and reliable way to predict the turbulent transport. However, quantitative transport estimates by the gyrokinetic simulations consume extremely heavy computational costs.

In order to reduce the costs of gyrokinetic simulations for quantitative transport prediction, we developed the scheme with the aid of the reduced transport model. In the scheme, the optimization techniques are applied to find the relevant input parameters for the nonlinear gyrokinetic simulations which should be performed to match the experimental transport fluxes and to optimize the reduced transport model for the plasma of interest. The developed scheme can reduce the computational costs to perform the quantitative estimate of the turbulent transport levels and the plasma profiles. Utilizing the scheme, the quantitative predictions for the turbulent transport can be realized by doing first-principle simulation once for each radial position.

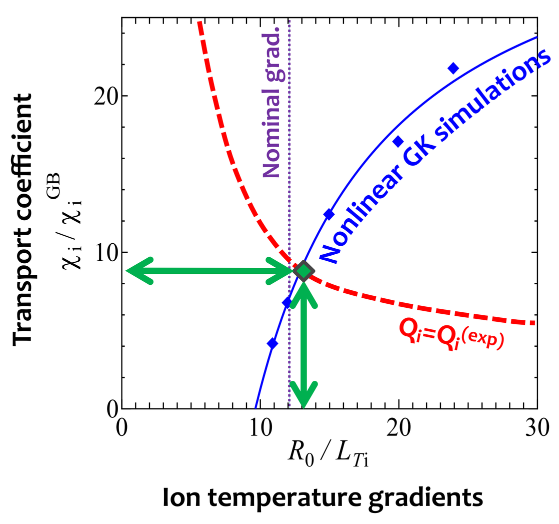
Introduction

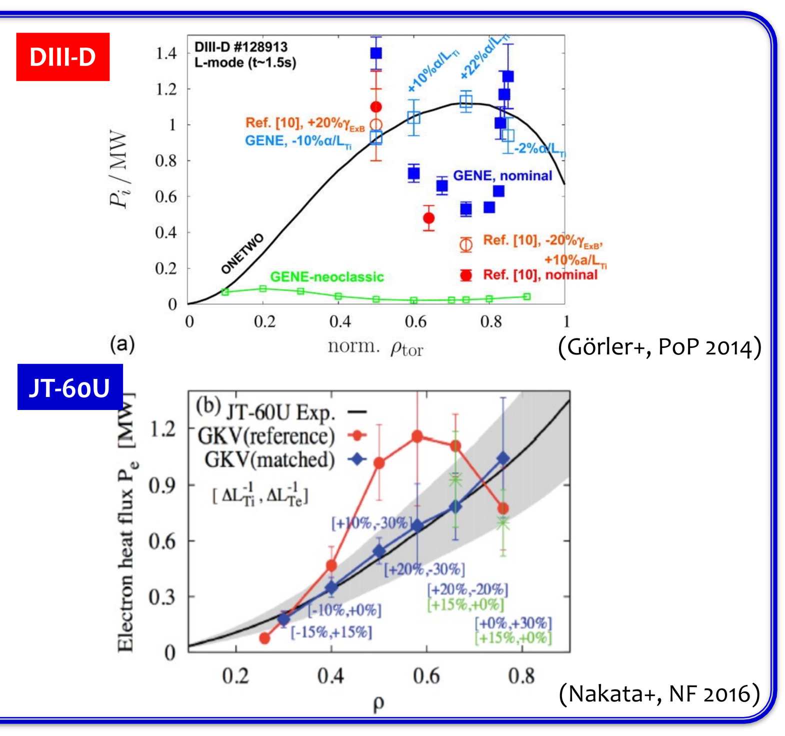
Turbulent plasma transport & Gyrokinetic simulation

- Plasma transport observed in experiments are much larger than the neoclassical transport. ⇒ **"Anomalous transport"**
- Anomalous transport is caused by turbulence driven by micro-instabilities.
- **Gyrokinetic (GK) model is powerful and reliable tool to estimate the transport as a first-principle approach.**

Flux-matching technique

- In (local) GK simulations, plasma profiles are treated as input parameters.
- If the profiles can be tuned to match the experimental fluxes, we can reproduce the fluxes by GK sims., quantitatively.
- For various experimental shots, GK simulations have been performed using the flux-matching technique.



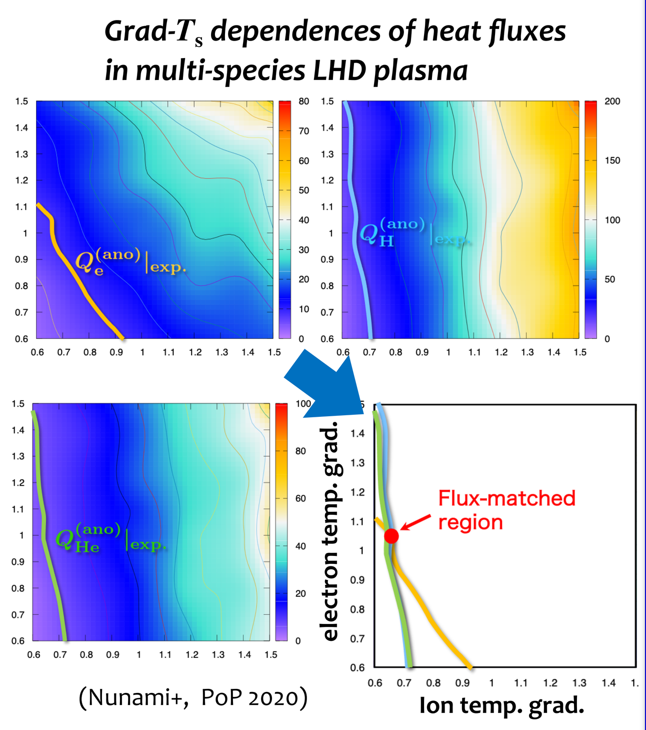


Issues in quantitative transport estimate

GK sims with flux-matching

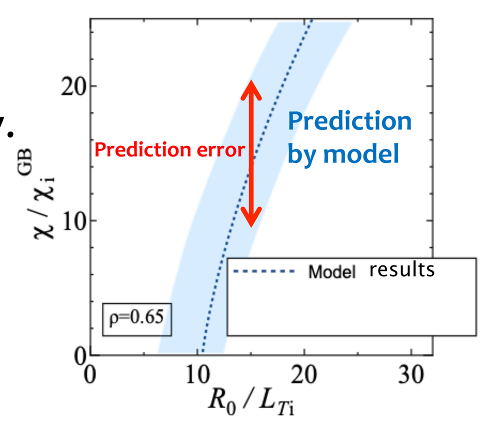
- NL GK simulations using flux-matching technique can reproduce the experimental transport fluxes, quantitatively.
- To obtain matched plasma profiles (inputs), we need many nonlinear (NL) GK runs. ex) In case of Q_i's and Q_e ; **> 30 NL runs!**
- For quantitative estimates with GK sims, numerous runs should be performed.

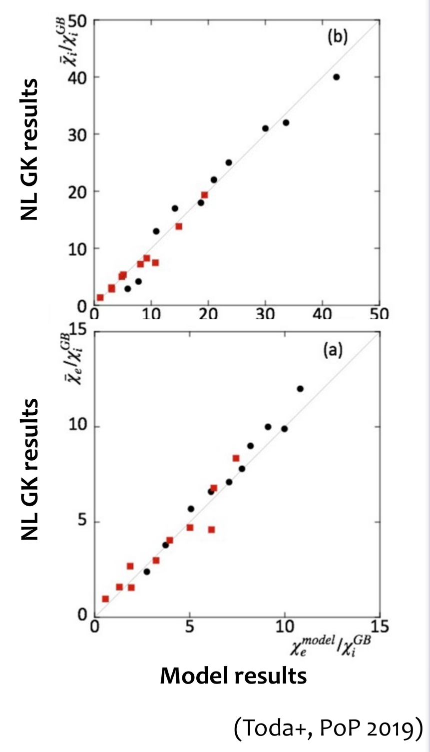
⇒ This is a crucial issue in quantitative transport prediction.



Reduced transport model to reproduce results of NL GK sims

- To clarify the dependences of transport flux on local params., based on many GK simulation results and/or linear analyses, the reduced transport model **which can reproduce the results of NL GK simulations** w/o additional nonlinear gyrokinetic runs.
- Reduced models have prediction errors, essentially.





⇒ This remains crucial issue in quantitative transport prediction.

➡ For quantitative estimates of turbulent transport, we have to reduce calculation costs with keeping prediction accuracies.

Procedure of the scheme

Start: A reduced transport model

Nunami et al., PoP 20, 092307 (2013)
Toda et al., JPCS 561, 012020 (2014)

$$\frac{\chi_i^{model}}{\chi_i^{GB}} = \frac{A_1 \mathcal{L}^{\alpha_0}}{A_2 + \tau_{ZF}/\mathcal{L}^{1/2}} \qquad \mathcal{L}(\rho) = a(\rho)\left[\frac{R}{L_{Ti}} - \beta_0 \frac{R}{L_{Ti}^{cr}}\right]$$

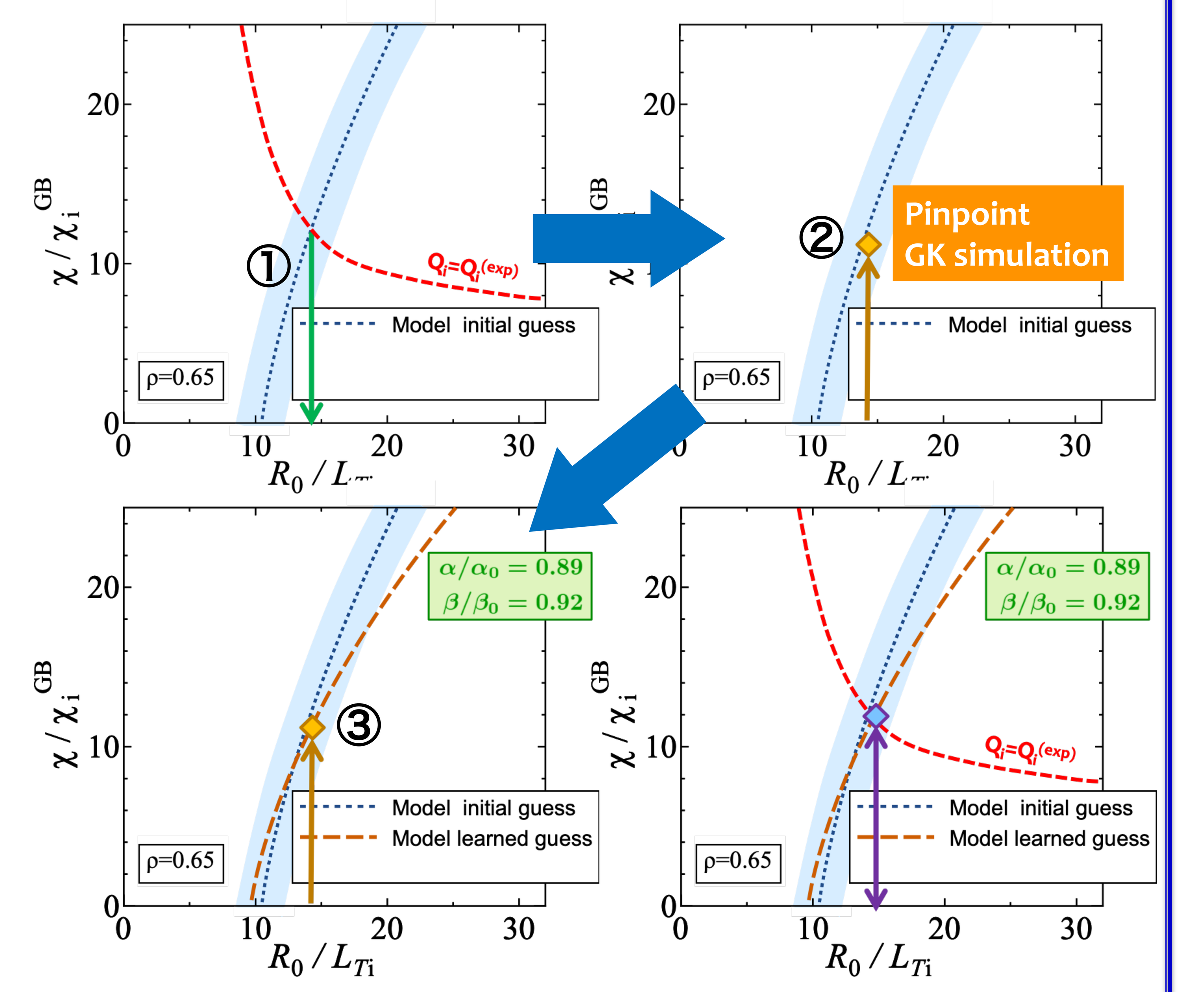
τ_{ZF} : Zonal flow decay time

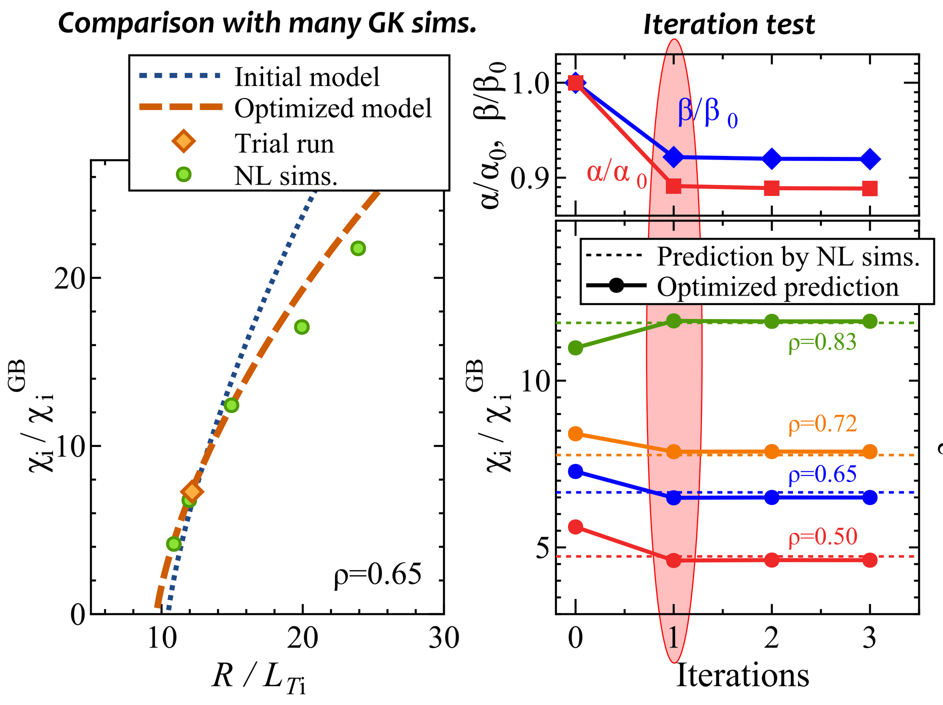
Procedure of the scheme

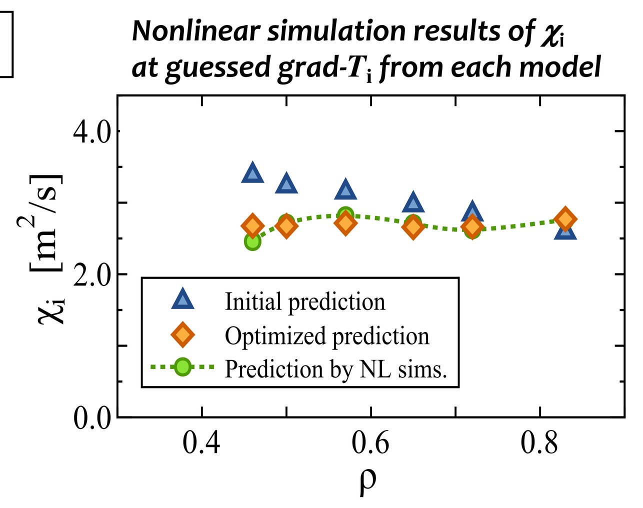
① From initial model, find the grad-T_i which matches with experimental flux by optimization technique.
Using **"GradientDescentOptimizer"**

② At the estimated gradient, we perform one NL GK simulation for each ρ.

③ Using the NL results, tune the parameters α_0 ➡ α and β_0 ➡ β, the model can be optimized.
Using **"AdamOptimizer"**







Relative errors against the first-principle nonlinear gyrokinetic runs

$$\sigma \equiv \sqrt{\frac{1}{n}\sum\left(\frac{\chi_i^{model}}{\chi_i^{GKV}} - 1\right)^2}$$

- w/ initial model only $\sigma_{inital} = 0.35$
- w/ optimized model $\sigma_{opt} = 0.095$

The developed scheme can reproduce profile dependences of transport coefficients from many GK simulations.
➡ We can predict turbulent transport fluxes keeping accuracies.

Application to transport analysis

Diffusion equation for ion heat

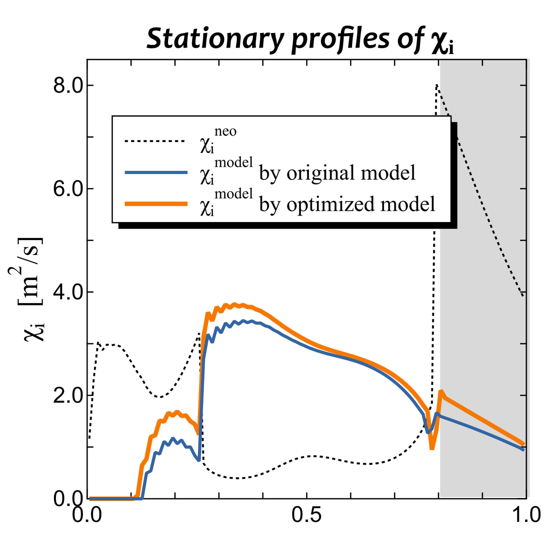
$$\frac{\partial}{\partial t}\left(\frac{3}{2} n T_i\right) = -\frac{1}{V'}\frac{\partial}{\partial \rho}(V' Q_i) + P_{hx} + P_{hi}$$

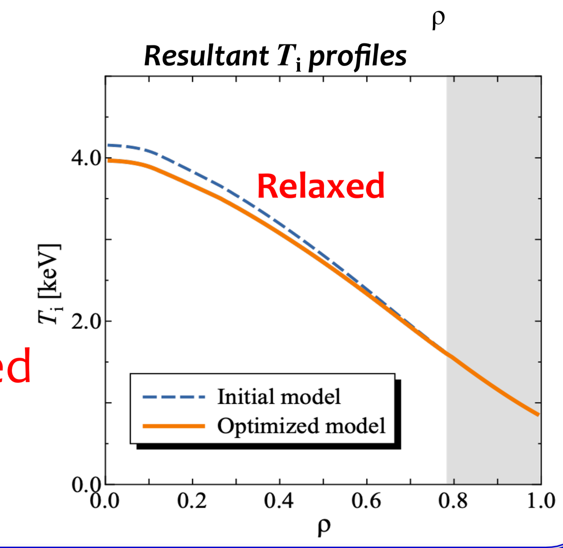
Ion heat flux; Heat exchange; Absorbed power

$$Q_i = -\langle|\nabla\rho|^2\rangle n_i \left(\chi_i^{turb} + \chi_i^{neo}\right)\frac{\partial T_i}{\partial \rho}$$

- Transport dynamics is examined for the LHD plasma using the modeled turbulent χ_i^{opt} instead of χ_i^{turb}, performing the integrated transport simulation by TASK3D code.
- Due to the slightly different heat diffusivities from both models, the resultant ion temperature profile can be changed.

➡ Using the optimized transport model by the developed scheme, we can perform the transport analysis with almost same accuracies of NL GK runs.





Summary

- For quantitative estimates of turbulent transport, we have to reduce calculation costs with keeping prediction accuracies.
- We developed new scheme to predict turbulent transport Combine first-principle sims, reduced transport model, and optimization technique.
- By GK runs as few times as possible, turbulent transport can be estimated with almost same levels of performing many GK runs..
- With almost same accuracies of GK runs, we can perform the transport analysis.

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