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SURROGATE MODEL OF TRANSPORT QUANTITIES OF GYROKINETIC SIMULATIONS ON HL-2A

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Abstract

Artificial intelligence (AI) and machine learning (ML) are increasingly pivotal in advancing magnetic fusion research. This study leverages nonlinear gyrokinetic simulations to systematically scan the plasma gradient parameter space for the HL-2A tokamak, generating datasets for electrostatic drift wave turbulence to train neural network (NN) and support vector regression (SVR) models. The developed surrogate models achieve high accuracy, with R^2 values of 0.90 for nonlinear transport coefficients. A novel two-stage framework is introduced: first, a local-profile surrogate model is constructed using a feedforward neural network (FNN) trained on 4267 samples; second, a support vector regression (SVR) model maps local predictions to global-profile turbulent transport, trained with 40 global simulation cases. This work highlights the potential of AI-driven surrogate models to enhance computational efficiency and accuracy in fusion research, offering a scalable approach for real-time control and scenario development in future fusion devices.

1. INTRODUCTION

Efficient, accurate, and reliable integrated modeling plays a crucial role in the design and operational control of magnetic confinement fusion devices. Among the physical processes involved in the integrated modeling, turbulent transport stands out as one of the most challenging components to predict due to its inherent complexities. The integration of artificial intelligence (AI) techniques such as machine learning into fusion research has emerged as a prominent direction[1], with growing efforts to construct surrogate models[2, 3]. However, the surrogate model based on gyrokinetic turbulence simulations remains scarce, primarily due to the prohibitive computational cost of high fidelity gyrokinetic simulations. Moreover, the infinite degrees of freedom inherent in parameter space further constrains surrogate model development, making brute-force gyrokinetic parameter scans practically impossible. This work proposes a methodology to map the results of local gyrokinetic simulations to global parameter space, thereby enabling the construction of a computationally efficient surrogate model that sufficiently capture the essential global physics. This approach may not only enables the development of a reliable surrogate model for global turbulent transport but may also leverage data from multiple reduced models or local simulations, significantly reducing dependence on expensive gyrokinetic simulations.

This study employs the gyrokinetic code GTC[4] (Gyrokinetic Toroidal Code) to perform high-fidelity simulations and parameter scans based on the HL-2A Tokamak experimental configuration. As a high-performance, high-accuracy particle-in-cell code, GTC exhibits exceptional parallel computing capability and predictive accuracy, enabling first-principles simulations of various instabilities in toroidal fusion devices. GTC simulations demonstrate excellent agreement with experimental observations and have successfully elucidated numerous Tokamak phenomena[5]. It is widely regarded as a highly credible and physically comprehensive numerical tool in the plasma physics.

This study employs two classical machine learning approaches: Neural Networks (NNs)[6] and Support Vector Machines (SVMs)[7] for data analysis and modeling. Neural Networks are biologically inspired multi-layer nonlinear models that optimize weight parameters through forward propagation and backpropagation algorithms. Capable of autonomously extracting complex features from high-dimensional data, NNs excel in solving nonlinear mapping problems. Support Vector Machines are supervised learning algorithms grounded in statistical learning theory. SVMs exhibit strong generalization capability for small-sample, high-dimensional scenarios while maintaining resistance to overfitting.

2. SCAN PARAMETERS

We conduct parametric simulations using the GTC code based on shot 27055 from the HL-2A[8] experimental device. The density $n_0 = 1.0{\times}10^{19}/m^3$, the temperature on axis $T_e = T_i = 2.0keV$, realistic mass $m_i/m_e = 1837$, safety factor $q = 1.4$ on the reference magnetic surface at $r = a/2$. We establish a three-dimensional parameter space by systematically varying three length scales, i.e., normalized density length scale R/L_n, normalized temperature length scales R/L_{Ti} and R/L_{Te}, while maintaining other equilibrium parameters unchanged. For each simulation case, we select eight equidistant radial points $r_1, r_2, ...r_8$ as spatial coordinates, accurately reflecting transport properties at different radial positions.

Two parameter space construction methods are employed. For local simulation approach, a super-exponential profile $R/L_s = Aexp[-((r - r_0)/w)^6]$ is adopted for profiles of the density and temperature scale lengths, ensuring constant scale lengths in the core simulation region. With this configuration, the sole degree of freedom for profile variation is the "pedestal" height. We uniformly sample 8 points along R/L_n, R/L_{Te}, and sample 10 points along R/L_{Ti}, constructing a parameter space comprising 768 (8×8×10) sample points. The HL-2A experimental profiles reveal a close resemblance to the function $A(\hat{\psi}) = 1 + c_1(tanh((c_2 - \hat{\psi})/c_3) - 1)$ distributions, where $A = n_e, T_i, T_e$, and $\hat{\psi}$ is the normalized poloidal magnetic flux. We generate a 50-sample n dataset of global scale length profiles by randomly varying the scale length peak amplitudes and positions around experimentally fitted profiles.

3. SURROGATE MODEL OF LOCAL PROFILE SIMULATIONS

We sample 8 points in each case alone different radial positions, and obtain $(R/L_n, R/L_{Ti}, R/L_{Te}, r/a, q)$ on each sampling points as input data. The number of dataset is expanded to 6096. The transport coefficients are normalized with the GyroBohm unit $D_{GB} = \frac{\rho_i}{R_0}\frac{T_e}{eB}$. The dataset was partitioned into training set(4,267 samples), validating set (914 samples) and testing (915 samples) sets with a 7:1.5:1.5 ratio. We built and tuned Forward Neural Network models of 1D quantities. The regression coefficient $R^2 > 0.9$ can be achieved on the test dataset for all the transport coefficients, i.e., ion thermal conductivity χ_i, electron thermal conductivity χ_e, and particle diffusivity D_i, as demonstrated in Figure 1, indicating the established turbulence surrogate model is able to accurately predict turbulent transport for local plasma profiles.

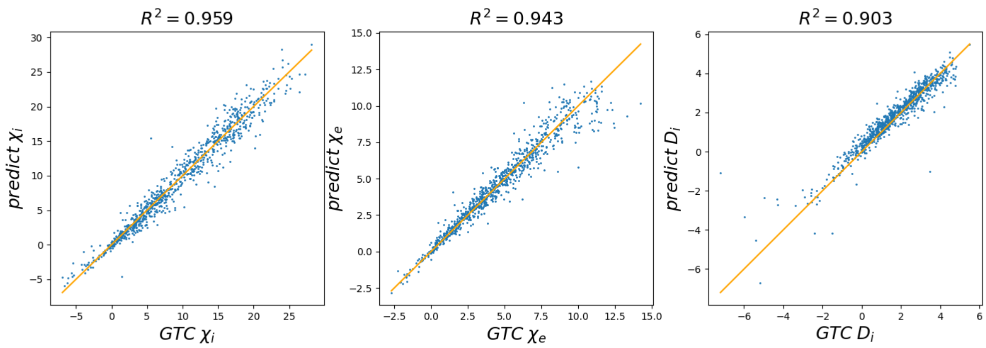

FIG. 1. Regression result of local profile simulation transport coefficients χ_i, χ_e, D_i. The $R^2 > 0.9$ for all the quantities indicates the well prediction results.

4. LOCAL-GLOBAL MAPPING MODEL

In this paper, we try to find a mapping model to transform the local profile surrogate model result to the global simulation results. Our working framework showed as Figure 2: (1) Large-scale local profile simulations generate the training dataset for a neural network-based local surrogate model; (2) Global simulations are performed to generate a realitive small dataset; (3) For cases in global dataset, the point-wise coordinates, profile parameters, and local model predictions served as input features for regressing global transport coefficients; (4) Systematic validation of model performance.

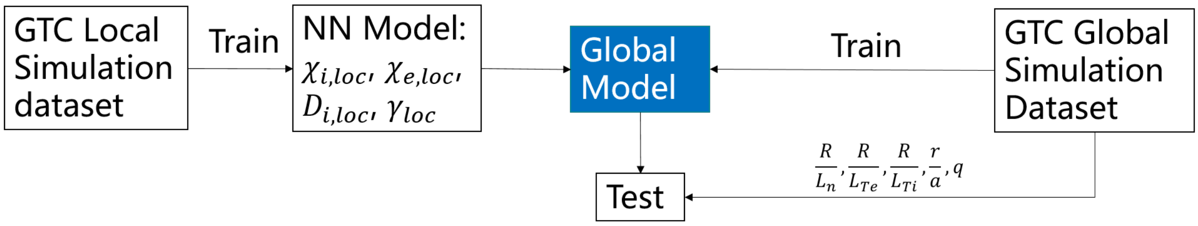

FIG. 2. The frame of building the Local-Global mapping model.

We employed support vector regression (SVR) method to connect the local profile simulation results with the global profile simulation results. For the SVR regression model, the input features include spatial coordinates, plasma gradients, and transport predictions from the local surrogate model for selected 8 radial sampling points, i.e., $R/L_n(r_j), R/L_{Ti}(r_j), R/L_{Te}(r_j), r_j/a, q(r_j), \chi_{i,local}(r_j), \chi_{e,local}(r_j), D_{i,local}(r_j)$, $j = 1, 2, .., 8$, while the output targets the transport coefficients at each radial position, i.e., $\chi_{i,global}(r_j), \chi_{e,global}(r_j), D_{i,global}(r_j)$, from the global gyrokinetic simulations using GTC. Among the 50 global profile simulation cases, 40 cases are used as the training set and the rest 10 cases are used as the test set. Fig. 4 presents a comparative analysis for a representative case: The local-global mapping model predictions (red dots) show excellent agreement with actual global simulation results (blue curve). The Mean Average Percentage Error (MAPE)s are all low for all three transport coefficients, also indicates the precise prediction of global profile simulation results. The predictions from the local surrogate model alone (green dots) exhibit substantial error from simulation results. These results not only validate the mapping model's effectiveness but, more importantly, reveal fundamental differences in turbulent transport characteristics between local and global simulations despite identical gradient scale lengths at identical positions - conclusively demonstrating the necessity and efficacy of developing such a mapping framework.

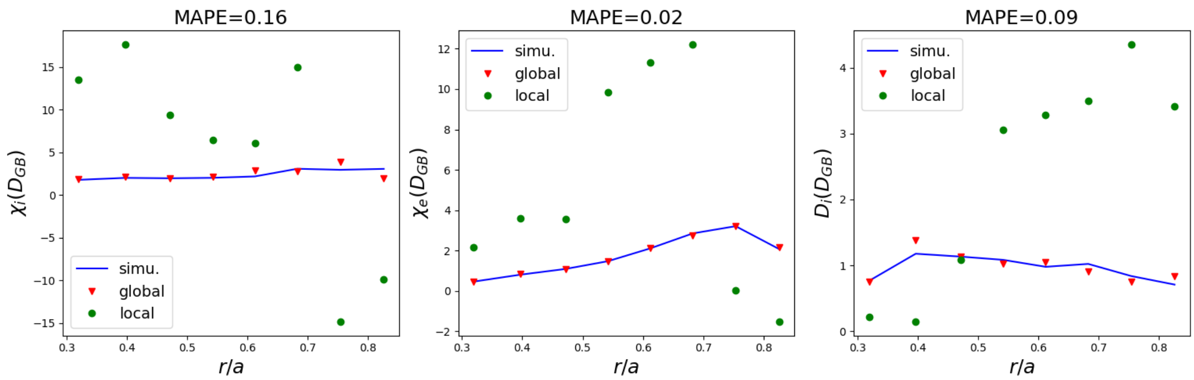

FIG. 3. The prediction result of Local-Global mapping model for one test case. The red dots, blue lines and green dots represents the Local-Global mapping model prediction, the global simulation prediction and the local model prediction, correspondingly. The MAPEs of three quantities are also shown as subtitles.

5. CONCLUSION AND DISCUSSION

This study presents a comprehensive framework for developing surrogate models to predict turbulent transport in HL-2A tokamak plasmas, combining high-fidelity gyrokinetic simulations with advanced machine learning techniques. The work successfully bridges the gap between local and global turbulent transport predictions through a novel two-stage modeling strategy. By first establishing a neural network-based surrogate model for local profile simulations (achieving R^2¿0.9 accuracy) and then developing a support vector regression mapping to global profiles. The methodology demonstrates remarkable computational advantages, reducing reliance on expensive full-fidelity gyrokinetic simulations while maintaining physical accuracy. The local surrogate model trained on 4267 samples and the global mapping model using only 40 cases suggest significant potential for accelerating integrated modeling workflows.This work establishes a valuable paradigm for combining first-principles simulations with data-driven approaches in fusion research. The methodology not only addresses immediate needs for efficient transport modeling but also provides a scalable framework that could incorporate additional physics complexity as computational resources allow. The demonstrated accuracy and efficiency suggest strong potential for application in scenario development, real-time control, and uncertainty quantification in future fusion devices.

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