9th Asia-Pacific Conference on Plasma Physics, 21-26 Sep, 2025 at Fukuoka

The low-dimensional representation of Quasi-helical stellarator geometries

Xishuo Wei[1], Handi Huang[1], Hongxuan Zhu[2], Haotian Chen[1,3], Zhihong Lin[1]
[1]University of California, Irvine [2] Princeton University [3]Peking University
e-mail (speaker): xishuow@uci.edu

Previous works proved that the stellarators with ‘quasi-symmetric’ (QS) geometries can be constructed in which the toroidal angular momentum is approximately conserved, and the single particle orbit loss is significantly reduced [1]. But for stellarator to be an attractive reactor concept, more physics optimization beyond the single particle orbit loss should be considered, such as the MHD instability and turbulent transport. Previous works have used heuristic criterion or local models to evaluate these more complicated collective modes. However, these local approximate estimations may not be reliable due to the intrinsically 3D geometries of the stellarators [2]. On the other hand, the first-principles global simulations are computationally expensive and difficult to integrate in the optimization process. A desirable alternative method is to use the fast machine learning based surrogate model [3] to replace the first-principles codes. However, the training of the surrogate model relies on the first-principles global simulation data covering the parameter space. Due to the high degree-of-freedom of the stellarator design, the parameter space can have a dimension of several hundreds. Here, we demonstrate that the QS geometries are distributed in a low-dimensional subspace. Thus, the amount of global simulation data required to train a surrogate model can be greatly reduced.

Over 10,000 equilibria with quasi-helical symmetry are generated by DESC[4] for the machine learning model training. We use the auto-encoder neural network to find the low-dimension parameter space (the latent space) where the QS geometries are distributed in. The input and output are the stacked 1-dimensional array of coefficients that describe the flux surface shapes, with a length of 765. In the middle of the network a layer of size s is used, and $s \ll 765$. The auto-encoder will minimize the difference between the input and output, so that the geometry can be effectively described by s parameters. We also use the distance of collocation points as part of the loss function to improve the reconstruction accuracy. The relative error of outputs on the test dataset has a dependence on the latent space dimension s. It is shown that the reconstruction error is smaller than 1% when $s \geq 3$, as shown in Fig 1. Both the coefficients and the flux surface shapes have a good agreement.

The capability of the 3-d space found by auto-encoder can also be demonstrated by predicting the Rosenblut-Hinton (RH) residual level of zonal flows in QH stellarators. Because of the strong suppression of turbulent transport by zonal flows, the RH level can act as an effective indicator of transport level. A new neural network is designed to predict the analytical RH level[5] in the QH geometry from the corresponding 3 coordinates of the 3-d latent space. The prediction is shown in Fig 2 and good agreement is achieved.

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It becomes straightforward to find a QH geometry with low turbulent transport. Two equilibria with RH level 0.21(Case584) and RH level 0.40 (Case364) are selected. The global turbulence simulation in the two geometries are carried out using gyrokinetic code GTC, and the heat transport and zonal flow shearing rate evolution are shown in Fig 3. Indeed, the geometry with higher RH level (Case364) has higher zonal flow shearing rate and lower transport level.

Our results demonstrate that the low dimensional representation of QS geometry can be found through machine learning. The low dimensional space is useful to analyze the zonal flow residual level and find the geometry with low transport level. This finding enables the generation of global gyrokinetic simulation data for training surrogate models to optimize the stellarator geometry with more complex physics.

References

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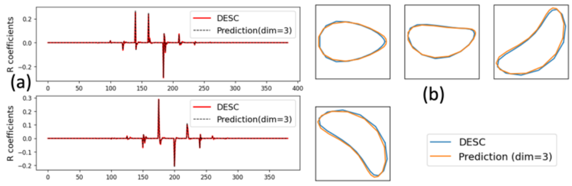

Figure 1 reconstruction of QH stellarator geometry.

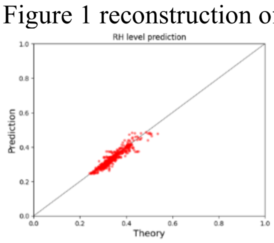

Figure 2 Camparion of predicted and theoretical RH level.

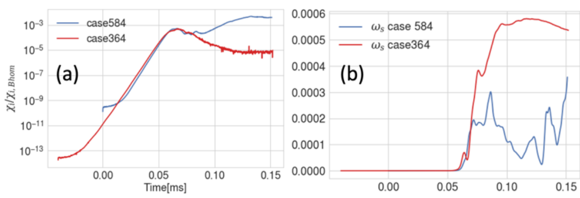

Figure 3 Transport level and ZF evolution for two selected geometries.