Artificial Intelligence generated surrogate model of plasma turbulence

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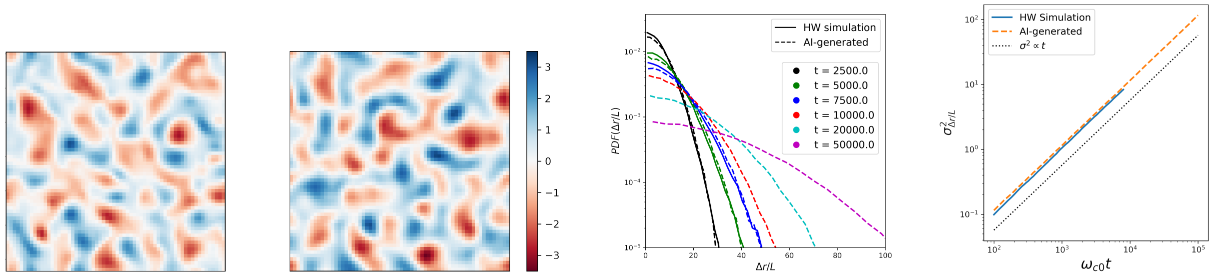
Turbulent transport plays a major role in confinement degradation, thereby limiting the performance of current and future fusion devices. Modelling turbulent transport requires long-time simulations which are limited by the computational resources available. One way to overcome this limitation is by using surrogate models that are computationally cheaper to evaluate. In this presentation we apply Artificial Intelligence (AI) methods to construct a surrogate model of plasma edge turbulence described by the Hasegawa-Wakatani (HW) system [1] and use the model to perform fast, long-time turbulent transport computations [2]. The proposed surrogate model is based on the combination of a convolutional variational auto-encoder (CVAE) [3] and a recurrent neural network (RNN). A convolutional network is used to encode snapshots of computed turbulence states into a reduce latent space, and a RNN is trained to reproduce the time evolution of turbulence in the latent space. Once the autoencoder is trained, new turbulence sates are obtained by decoding the latent space dynamics generated by the RNN. Panel (a) in Fig.1 shows a snapshot of the electrostatic turbulent fluctuation from a numerical solution of HW. Panel (b) shows a statistically similar CVAE-generated turbulence state. Panels (c) and (d) show the agreement between the Lagrangian statistics of particle transport (probability distribution function and diffusive scaling) computed using HW turbulence (solid lines) and the statistics obtained with the 500-times faster proposed AI-algorithm (dashed lines) combining the generative power of CVAE and the time predictive capabilities of RNN.



(a) HW simulation (b) AI generated (c) Δr PDFs (d) Δr variance

Figure 1

References

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