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Surrogate mode of 2D turbulence with physics-informed neural networks

J.C Huang[1], Z.S Qu[1], R. Varennes[1], X. Garbet[1,2], C. G. Guet[1], D. Niyato[3], V. Grandgirard[2],
[1] SPMS, NTU, 637371 Singapore. [2] CEA, IRFM, F-13108 Saint Paul-lez-Durance.
[3] CCDS, NTU, 639798 Singapore.
email: Huan0366@e.ntu.edu.sg

Surrogate models are becoming increasingly pivotal in contemporary physics, particularly in domains where numerical solutions are challenging due to the complexity of non-linear effects, such as fluid dynamics, plasma physics, and chaos theory [1]. These models alleviate computational burdens by capturing the relationships between inputs and outputs, often by simplifying the system through observational data. [2,3] Deep learning, in particular, has proven to be an effective tool for this purpose, demonstrating significant potential in learning high-dimensional non-linear effects, even though successful examples of its application to complex nonlinear functions are still relatively few.

As a first step in developing fast and accurate surrogate models of turbulence transport, our objective is to utilize Physics-Informed Neural Networks (PINNs) to develop a forward solver for the Hasegawa-Wakatani (HW) equations [4]. By providing the model solely with the equations and the initial conditions in the linear stage, we aim to predict the turbulent electric field and plasma density. Reference data are produced by the direct numerical solver TOKAM2D, a 2D spectral code capable of simulating edge fluid turbulence including the HW equations.

In this work, multiple new variants of PINN are tested, including Fourier embedding layer [2], Fourier special penalty, causal time stepping **[5],** etc. Although some of these methods boost convergence during training, they fail to capture the nonlinear evolution of turbulent vortices. Moreover, the performance of PINN degrades in fitting high-order derivatives. These results provide valuable clues to further improve learning the complex nonlinear dynamics.

References

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