Neural network surrogate modelling of tokamak turbulence

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Plasma energy losses due to turbulent transport in toroidal magnetic confinement devices, such as tokamaks, is one of the limiting factors for achieving viable fusion energy. Reactor design and plasma scenario optimisation demands both accurate and tractable predictive turbulence calculations. High-fidelity direct numerical simulations of plasma turbulence require 10-100 MCPUh to resolve plasma evolution on discharge timescales, making routine tokamak scenario prediction infeasible. Neural network surrogate physics models provides a pathway to circumvent the conflicting constraint of accuracy and tractability. A key enabling step is the development of reduced order turbulence models, such as QuaLiKiz [1,2], which are $\times 10^6$ faster than nonlinear simulations and can model discharge timescales within $\sim$100CPUh. Codes like QuaLiKiz provide routine capability to predict tokamak temperature, density, and rotation radial profiles, and extrapolation to future machine performance. However, the computation timescales are still insufficient for extensive scenario optimisation and control-oriented applications. This additional step is provided by neural network surrogate modelling. The computational speed of reduced turbulence models such as QuaLiKiz is sufficient for the construction of extensive databases of model input-output mapping using HPC resources. These databases are then used as training sets for neural network regression. A key aspect is the customisation of output regression variables and optimisation cost functions in a physics-informed manner, to capture known features of the system. The resultant neural network transport model is an accurate representation of the QuaLiKiz model, and can provide near-realtime tokamak transport predictions. We provide an overview of the state-of-the-art in QuaLiKiz NN surrogate development, ranging from grid-based input-space approaches [3], sampling input space based on fitting of pre-selected experimental databases [4] including clustering and data-reduction approaches, and modification of the neural network topologies themselves to better capture the structure of the input-output mapping. These advances open up new possibilities for first-principle-based scenario optimization, control-oriented applications, and uncertainty quantification, hitherto constrained by the bottleneck of turbulent transport model computations.

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