Using feed-forward neural networks in real-time capable turbulent transport modelling

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Quasilinear gyrokinetic models have been very successful in predicting particle and heat transport in tokamaks, and in reproducing experimental profiles in many cases. One such code is QuaLiKiz, a reduced model used to successfully reproduce JET, ASDEX-U and Tore-Supra profiles [1, 2, 7]. While QuaLiKiz is already very fast, 1s of JET evolution demands $\sim 2.10^3$ turbulent flux calculations, resulting in $\sim$ 10 hour simulation time for a second of plasma evolution. Using neural networks as a surrogate turbulence model, the computational cost can be reduced 5 orders of magnitude, allowing for scenario optimisation and real-time applications. In this work, we use a large database of 3.10^8 flux calculations over a 9D input space generated with the QuaLiKiz code to train feed-forward neural networks.

The input space is an extension of the 4D input space of the networks successfully implemented in the RAPTOR rapid profile evolution code [3, 4]. We extend the ion temperature gradient R/L_{T_i}, ion-electron temperature ratio T_i/T_e, safety factor q and magnetic shear $\hat{s}$ with the electron temperature gradient R/L_{T_e}, density gradient R/L_n, minor radius ρ, collisionality ν^*, and Z_{eff} as well as rotation shear γ_E using a generalised ExB turbulence suppression rule in post-processing [5].

Training is done with the powerful TensorFlow framework, automated using the Luigi pipeline manager. This approach allows for simple extension to for example networks over a larger dimensional input space, trained on the experimentally relevant subspace [6].

The networks allow for transport simulations at a speed that is unprecedented, and opens new avenues in the modelling of fusion experiments.

References

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