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Using neural networks for real-time capable turbulent transport modelling

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Predicting transport in fusion devices is important to interpret and optimize current experiments, and extrapolate to future machines. Quasilinear turbulent transport models have been very successful in predicting particle and heat transport in tokamaks, successfully reproducing experimental profiles in many cases. One such code is QuaLiKiz, a reduced model which has been successfully validated against JET, ASDEX-U and Tore-Supra profiles [1,2,3,4]. While QuaLiKiz is already 6 orders of magnitude faster than non-linear gyrokinetic simulations, integrated modelling simulations of 1s of JET evolution still demands ~10 hour simulation time parallelised over 10 cores. Using neural networks as a surrogate turbulence model, the computational cost can be reduced up to 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 [5,6]. 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, local inverse aspect ratio ρ/R, collisionality $\nu *$¿, and Z_{eff}. Rotation shear γ_e is added as a 10th dimension using a generalised ExB turbulence suppression rule in post-processing [7]. 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 [8]. In the training and validation, extra care is given to maintaining physical constraints of the underlying model, while sacrificing as little network evaluation speed as possible. The main considerations are related to the ETG, ITG, and TEM instablity threshold. This threshold needs to be well-captured and sharp, and should be at exactly the same for all transport channels. Aditionally, no residual fluxes should be predicted by the network in regions where QuaLiKiz predicts zero flux [9].

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

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