First multi-channel core transport simulations with RAPTOR using a neural network transport model

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The calculation of turbulent transport is a significant bottleneck for integrated modelling of tokamak scenarios. Fast and accurate core turbulence transport models are vital for various applications such as: efficient offline tokamak scenario preparation and optimization, discharge supervision, realtime trajectory optimization.

Significant speedup is achieved through the quasilinear approximation, valid when $\delta n/n \sim O(\%)$. This is typically the case in the confined region within the last closed flux surface [1]. While 6 orders of magnitude faster than nonlinear simulations, quasilinear models still require $\sim$10 CPU seconds for a flux calculation at single radial point. This is sufficient for for integrated modelling, leading to $\sim$100 CPUh for 1 second of plasma evolution on a JET-scale device. However, it's still far from realtime and efficient scenario optimization applications.

Our approach to circumventing the conflicting constraints of accuracy and tractability is the following: apply quasilinear models to construct large-scale transport flux databases in experimentally relevant parameter space. Then, sift from these databases training sets for neural network regression. The neural network transport model is then realtime capable.

For this purpose, we apply the QuaLiKiz gyrokinetic quasilinear transport model [2, 3, 4]. For recent QuaLiKiz validation in ASDEX-U and JET, see [5].

An existing multilayer perceptron neural network (NN) proof of principle for regression of QuaLiKiz output [6] with 4D input has now been extended to include kinetic electrons. The input range is shown below in table 1. It consists of a reduced 4D database of QuaLiKiz results, valid for ITG turbulence regimes. These dimensions are $R/L_{Ti} \equiv -\frac{R}{T_i}\frac{dT_i}{dr}$, safety-factor q, magnetic shear $\hat{s}$, and ion to electron temperature ratio T_i/T_e. 16 ion-scale wavenumbers are in-

Table 1: Summary of input parameters for the QuaLiKiz kinetic electron ITG database employed in this work

Parameter	Min value	Max value	No. of points
R/L_{Ti}	2	12	30
T_i/T_e	0.3	3	20
q	1	5	20
$\hat{s}$	0.1	3	20
$k_\theta \rho_s$	0.05	0.8	16
Total no. of points			3 840 000

tegrated over. The database consists of dense uniform input grids, with $\sim$ 50000 unstable points used in training sets. The NN transport model developed from regression of this database is named QLKNN-4Dkin.

The NN outputs are ion and electron heat flux, electron particle diffusivity and pinch. Extensions of this database and NN fitting to 9D and beyond are ongoing [7].

The QLKNN-4Dkin transport model is coupled to the control-oriented RAPTOR tokamak simulation suite [8]. The use of the NN as a transport model is applicable for the implicit PDE solver within RAPTOR, due to the availability of analytical derivatives of the NN outputs with respect to the RAPTOR simulation state variables.

RAPTOR is now upgraded to include simultaneous T_e, T_i, density and poloidal flux evolution. We now describe the first self-consistently coupled T_i and T_e simulations using RAPTOR, in conjunction with a first-principle-based transport model. These simulations consist of validation of QLKNN-4Dkin on ITER and JET simulations.

For the ITER simulation, we compare RAPTOR/QLKNN-4Dkin to previous CRONOS/GLF23 modelling of the ITER hybrid scenario [9, 10, 11]. GLF23 and QuaLiKiz are comparable in a pure ITG regime. The comparison, during flattop following 300 s of plasma evolution, is shown in figure 1. The key point is that RAPTOR/QLKNN-4Dkin is faster than realtime, taking 20s to calculate 300 ITER seconds. CRONOS/GLF23 took 48 hours. This is a $\sim$ 4 order of magnitude speedup. However, this speedup was not only due to the transport model, even if that was the primary bottleneck. The RAPTOR equilibrium and heat sources were prescribed.

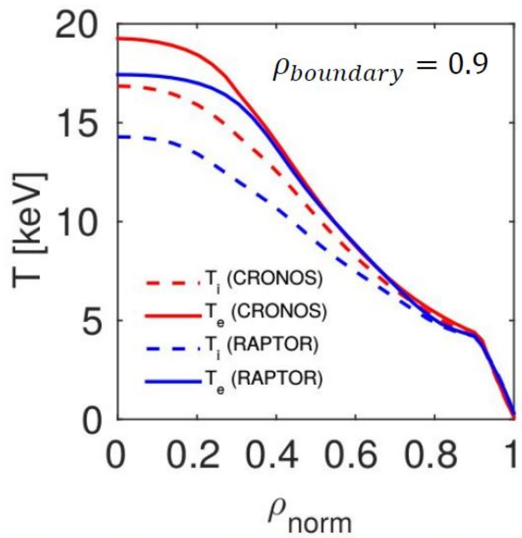

Figure 1: *Comparison of RAPTOR/QLKNN-4Dkin with CRONOS/GLF23 for an ITER hybrid scenario extrapolation*

For JET, QLKNN-4Dkin was then benchmarked between CRONOS and RAPTOR for baseline H-

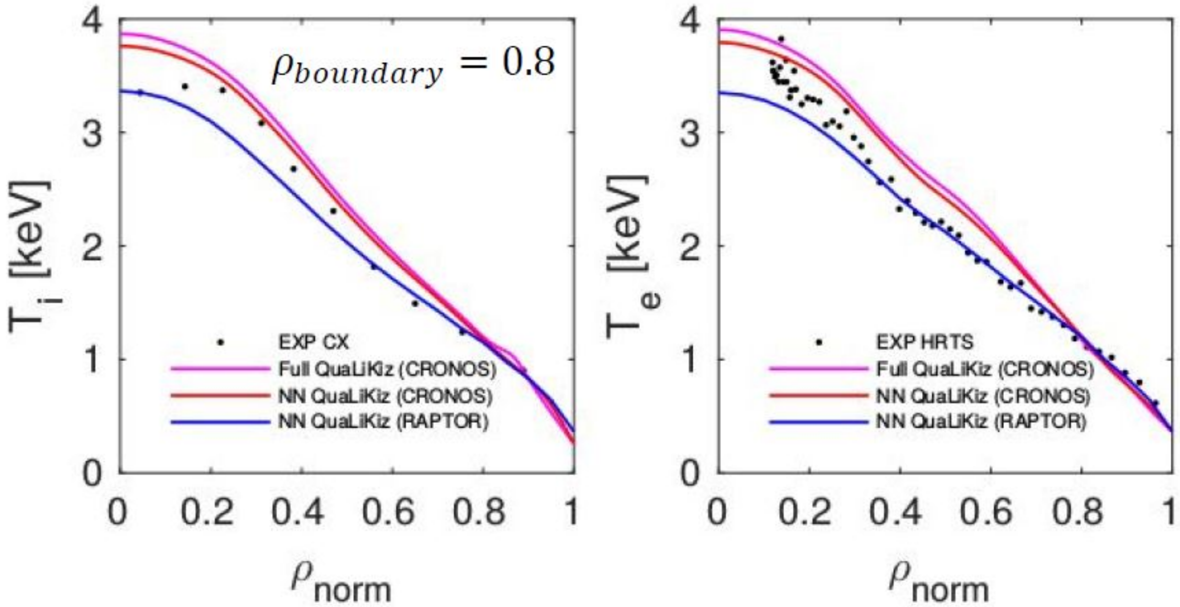

Figure 2: *Comparison of CRONOS/QLKNN-4Dkin with RAPTOR/QLKNN-4Dkin for JET H-mode baseline discharge 73324*

mode 73324 at flattop [12]. This is shown in figure 2. RAPTOR/QLKNN-4Dkin was again faster than realtime, needing 2s to calculate 4 JET seconds. This is unprecedented for first-principle-based integrated modelling. CRONOS/QLK took 100CPUh. This is a ~ 5 order of magnitude speedup. However, we again stress here that in CRONOS the equilibrium and heating sources were self-consistently predicted. In the RAPTOR simulation these were prescribed. The remaining $\sim 10\%$ RAPTOR vs CRONOS discrepancies in this case are to be investigated, and may lie in differences in the equilibrium.

This validation work has uncovered an interesting and challenging aspect of the neural network fitting, that of 'threshold matching'. Since the neural network transport model consists of two separate nonlinear mappings of q_i and q_e, there is no forcing that the ITG thresholds exactly match. See figure 3 for the statistics of threshold mismatch throughout the 4D NN.

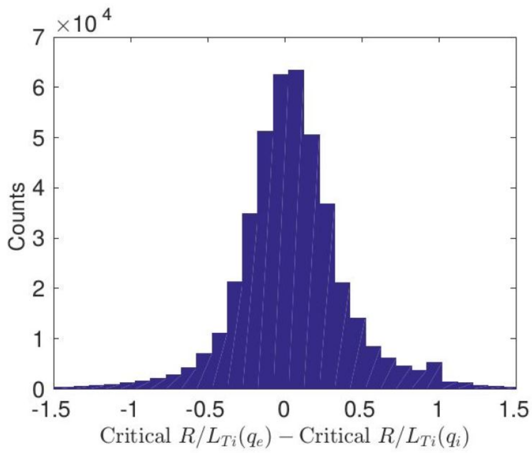

Figure 3: *Comparison of critical thresholds for q_i and q_e throughout the entire QLKNN*

While the critical threshold mismatch observed between q_e and q_i is typically low in relative terms ($< 5\%$), this can still lead to non-physical states due to profile stiffness. To alleviate this, we have employed a tunable bias to the input R/L_{Ti} in the q_e

critical threshold. This is needed to avoid $q_e = 0$ for a case where R/L_{Ti} is already fixed through flux balance. Since this is only an ITG transport model, there is then nothing to balance the source q_e apart from electron-ion heat exchange, and the T_e profile can thus run away. This is shown in figure 4. A potential solution is to fit NN outputs of $q_e + q_i$ and q_i/q_e, instead of to q_e and q_i directly. This ensures threshold matching, and such training is in progress.

To summarize, we have shown the first ever RAPTOR predictive T_e+T_i simulations. These were employed for validation of a proof-of-principle neural network turbulent transport model based on QuaLiKiz. This leads to faster than realtime capabilities. The validation was comprised of comparison to a ITER hybrid scenario simulation using CRONOS/GLF23, and a JET H-mode simulation using CRONOS/QLKNN-4Dkin.

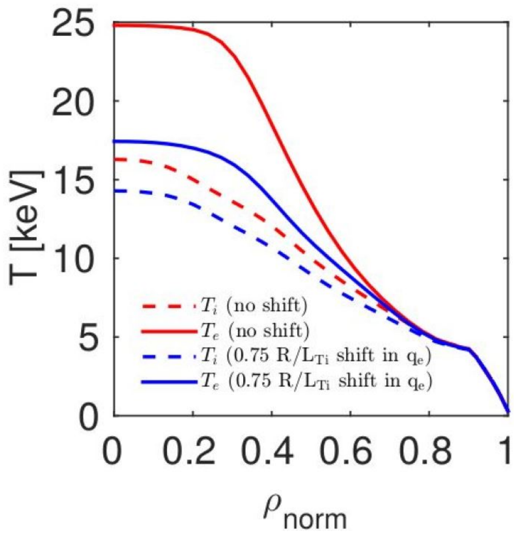

Figure 4: *Sensitivity test to R/L_{Ti} bias in the electron heat flux, for the RAPTOR/QLKNN-4Dkin ITER hybrid scenario modelling*

Regarding the JET benchmark with CRONOS, $\sim$ 10% discrepancies remain for T_e and T_i, and are to be investigated. A full benchmark including density prediction is also planned.

Work is ongoing to generalize the QLKNN transport model to higher dimensions. This will be employed within RAPTOR for scenario optimization and realtime monitoring applications.

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