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Fast surrogate modelling of turbulent transport in fusion plasmas with physics-informed neural networks

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Accurate prediction of tokamak core plasma temperature and density is essential for interpretation and preparation of current-day fusion experiments, optimization of plasma scenarios, and designing future devices. Transport of energy and particles, particularly in the tokamak core, is often driven by plasma micro-instabilities. Calculating this transport from first principles, for example using non-linear gyrokinetic codes, is too computationally expensive for routine simulation of tokamak discharge evolution.

In this work we present a method able to simulate a tokamak discharge in real-time, based on surrogate modelling. We first generate a massive database of $1.6\text{x}10^9$ flux calculations of the quasilinear gyrokinetic transport model, QuaLiKiz[4,5,6] acquired with HPC resources. The database spans a wide regime of plasma parameters, improving upon previous work[1] by including impurity density gradient scans of representative plasma impurities, as well as transport coefficients of light and heavy impurities instead of only the main ion. A Feed-Forward Neural Network based surrogate model is then trained on this database. We show generic neural network training is insufficient to correctly capture known physical features of tokamak turbulence, such as sharp instability thresholds common to all transport channels. We incorporate these features directly in the training process using two different methods: Customization of the cost function and training targets as shown in Fig (a); A novel late-fusion technique to include the features directly in the surrogate model architecture as shown in Fig (b).

(a) (b)

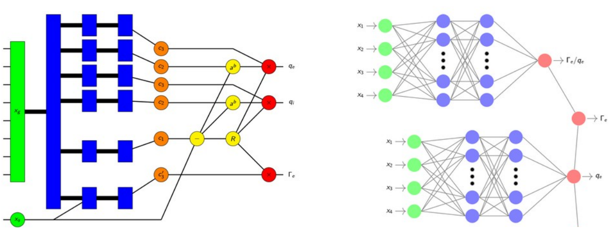

Fig. 1. Example of Neural Network structures with (a): late-fusion technique[8]; (b) customized cost function and training targets[1].

The surrogate turbulent transport model is applied within the rapid plasma transport simulator RAPTOR[2] and JINTRAC[7]. The predictions of temperature and density evolution of JET plasmas are in excellent agreement with the original QuaLiKiz model, yet orders of magnitude faster. This allows us to simulate plasma evolution in real-time, which is unprecedented for dynamic first-principle based transport simulations. This opens up a plethora of novel applications in tokamak design, scenario optimization, and control. Beyond core turbulent transport, our methodology is generally applicable for surrogate model generation throughout the integrated modelling landscape, enabling accurate and tractable full-device tokamak simulation, a longstanding Grand Challenge in the fusion simulation community.

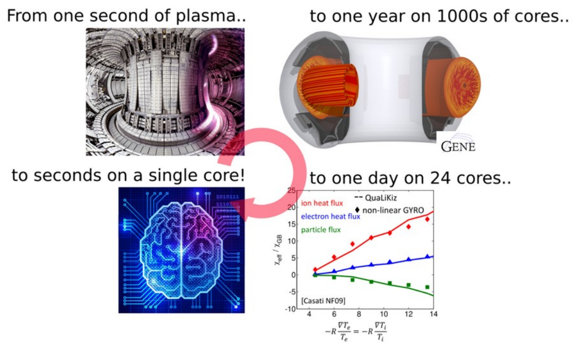

Fig. 2. Conceptual workflow as presented in Ref 1. From experiments (JET), to a physics rich computationally expensive model (GENE), to a reduced model based on extracting important physics (QuaLiKiz) to a neural network surrogate model (QLKNN).

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