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Neural surrogate models of core turbulent transport

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Model-based plasma scenario development often includes only simplified reduced-order models, deeming higher fidelity models too slow for iterative applications. Even then, low fidelity models are still too slow for pulse design in DEMO-class reactors. For instance, a single transport simulation for the STEP ramp-up (>2000s) with the TGLF quasilinear model can take several weeks. Conducting optimisation strategies such as Bayesian Optimisation can therefore be extremely costly despite the theoretical sample complexity guarantees that Bayesian Optimisation can offer. Neural network (NN) surrogate models of quasilinear core turbulence have been devised in the past years [1]. In the first part of this work, I will show how a neural network of the turbulent transport code TGLF allows to reduce the simulation time for the STEP ramp up to a few hours, enabling more queries in the pulse optimisation loop.
The generation of large simulation databases is unfeasible for computationally expensive models. Previous work by the authors [2] adopted Active Learning, a strategy that queries the physical model only in regions where additional data would improve the NN performance, and demonstrated a factor of 10 in data efficiency gains compared to random sampling. However, that study was limited to sampling according to the NN uncertainty, which suffers from lack of diversity in each acquisition batch. I will present benchmarks of several other acquisition functions on datasets from QuaLiKiz in the JET space. Contextually I will also present a TGLF NN for the JET space that complements previous work on obtaining NNs for the QuaLiKiz model [3].
Active Learning is applied to a streaming scenario relevant to power plants, as follow. Although constrained by empirical and theory-based extrapolations, the range of plasma states achieved by a machine is in general not fully known at the outset of operations. On the route towards maturation of operations in fusion power plants and reactor-relevant experiments such as ITER, a data stream is produced, which can be exploited in a digital twin infrastructure. In this framework, surrogate models based on previous experiments in the stream can be used to inform future campaigns for, e.g., optimisation tasks. The subsequent experimental achievement of more complex and performant plasma scenarios may result in both an increasing volume in parameter space and changing data distributions, thus requiring the acquisition of new simulation training data to update the surrogate. Active Learning has been applied to this setting. As a demonstration of a reactor relevant scenario, a mockup sequence of experimental campaigns was devised by sampling historical JET data at increasing values of W_{MHD}, and where QuaLiKiz is the base model. Preliminary results show the benefit of Active Learning strategies over random sampling in terms of data efficiency.

References

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