JET 1D tokamak plasma profile database construction for training neural network surrogate transport models

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Training set construction

Accurate and fast prediction of plasma turbulent transport properties is crucial for the design and operation of future fusion tokamak reactors. Gyrokinetic (GK) theory currently provides the most complete description of plasma turbulent processes, but nonlinear GK codes remain intractable for these applications. Recent work has applied neural network (NN) regressions to emulate reduced GK models, such as QuaLiKiz [1], showing promising results in terms of bridging this speed gap [2, 3]. This study extends previous work done on the NN regression of QuaLiKiz [4] by including additional input parameters, such as plasma rotation via M_{tor} and $R/L_{u_{\text{tor}}}$, Shafranov shift via α_{MHD}, and a second impurity species to disentangle main ion dilution from Z_{eff}, represented by $n_{\text{imp,light}}$. This is intended to improve the applicability of the NN predictions to a larger variety of plasma scenarios. As the number of dimensions increase, the number of data points increases exponentially if a grid-like parameter scan is used to populate the training set [4]. By extracting these input parameters from experimental data, this issue can be circumvented while simultaneously remaining close to relevant parameter subspace.

Experimental plasma measurements from discharges at the JET tokamak plasma device were extracted. The selected discharges are based on the JETPEAK database [5] but the time windows were chosen to adequately represent a wide variety of plasma scenarios, including current ramp-up and ramp-down phases. These profile measurements were then fitted using Gaussian Process Regression (GPR) techniques [6, 7]. The primary use of this database is to sufficiently populate a local dimensionless input parameter training set to perform exploratory development of NN turbulent transport model surrogates, within relevant accessible experimental subspace.

Each experimental time window in the profile database was sampled from $\rho_{\text{tor}} = 0.2 - 0.9$ in increments of 0.1 to produce the training set inputs, resulting in a data set of $\sim 10^5$ individual sets of inputs for GK simulations. The QuaLiKiz model was then executed using these points as inputs to generate the input-output pairs needed for supervised regression NN training. Figure 1 shows the distributions of the 15 chosen QuaLiKiz input parameters within the extracted training set where the plasma was sufficiently diagnosed to estimate all of the required inputs, e.g. where charge exchange measurements were available for T_i and rotation data. Approximately 15% of the collected data falls within this category. The shaded area represents the distribution of the input parameters in which QuaLiKiz predicted completely stable solutions, ie. no unstable ITG, TEM, or ETG modes were found.

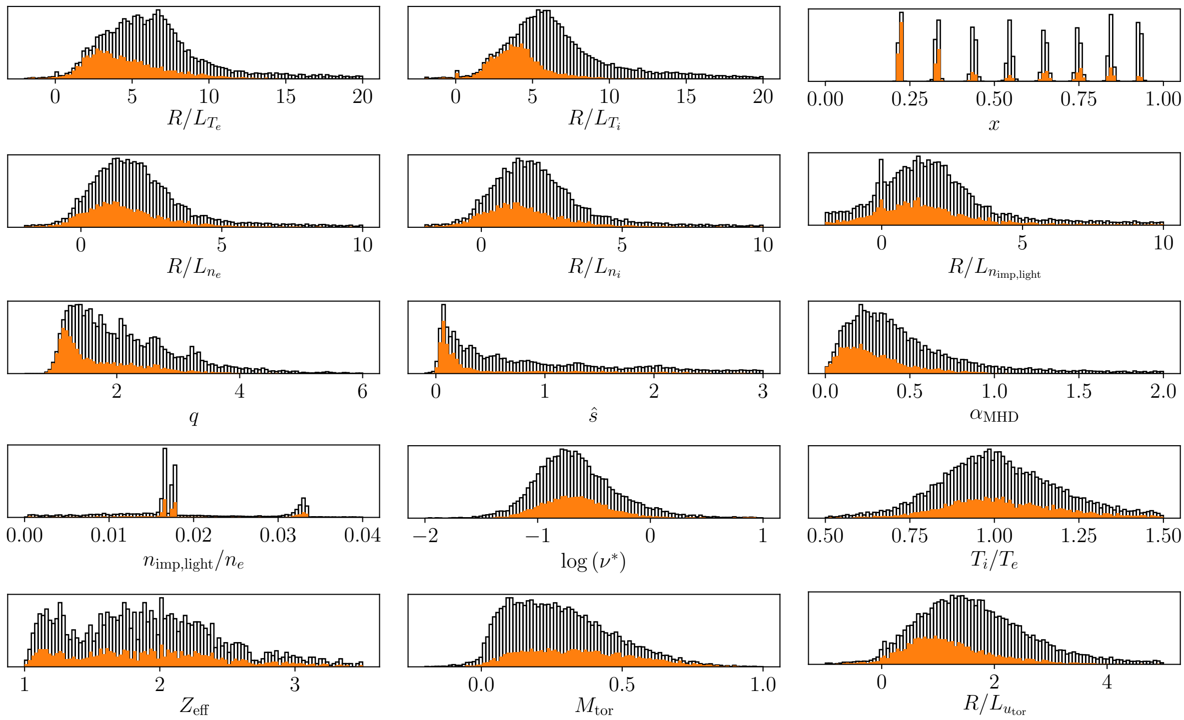

Figure 1: QuaLiKiz input parameter distributions for the data set completely characterised by available experimental data. $T_i = T_{\mathrm{imp}}$ was assumed for the construction of this data set. The main ion densities were estimated via quasineutrality, using the measured light impurity ion density, an assumed heavy impurity species (either tungsten or iron) and a flat Z_{eff} profile.

Figure 2 shows the same information as Figure 1 except with the remaining 85% of the data. For the missing data, $Z_{\mathrm{eff}} = 1.25$, $T_i/T_e = 1$, and $M_{\mathrm{tor}} = R/L_{u_{\mathrm{tor}}} = 0$ were assumed throughout the data set. As expected, both data sets show that plasma regions with low normalised gradients do not generally exhibit turbulent transport. Within the JET tokamak, this area is predominantly found in the inner core ($x < 0.4$) where sawteeth activity is often found. There is also a cluster of stable points for $x > 0.9$ within the incomplete data set, which also contains a larger proportion of ohmic L-mode plasmas and transient plasmas.

Although the data representations in Figures 1 and 2 provide a compact overview of the data set and the corresponding QuaLiKiz results, it is presumptious to draw strong conclusions about turbulence behaviour in tokamak plasmas directly from them. For example, both figures

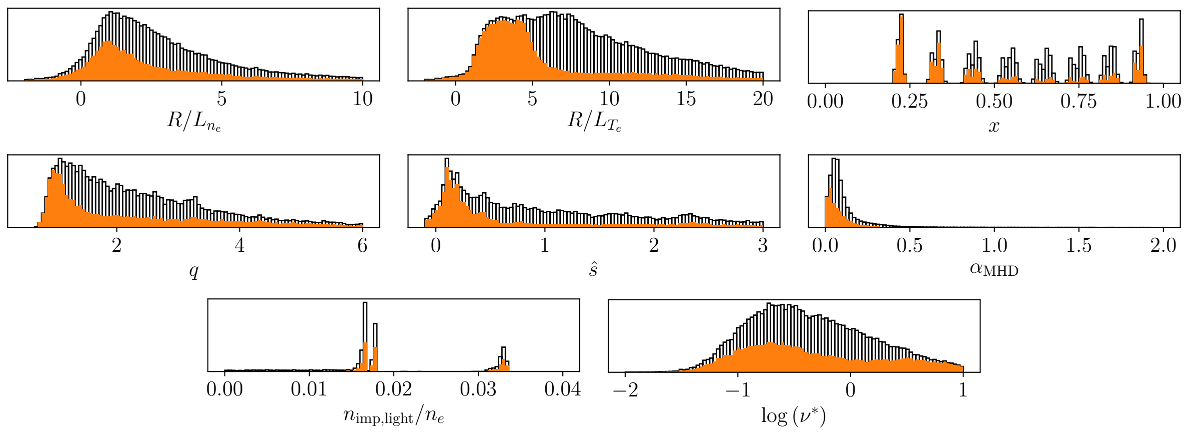

Figure 2: QuaLiKiz input parameter distributions for the data set with incomplete experimental data. Where data was missing, $Z_{\mathrm{eff}} = 1.25$, $T_i/T_e = 1$, and $M_{\mathrm{tor}} = R/L_{u_{\mathrm{tor}}} = 0$ were assumed. As a result, $R/L_{n_{\mathrm{imp,light}}} = R/L_{n_i} = R/L_{n_e}$ and $R/L_{T_i} = R/L_{T_e}$ for the majority of the data set and their distributions are not shown for brevity.

imply that stability is strongly associated with low values of magnetic shear, $\hat{s}$, which is not expected [8]. Instead, these data points coincidentally lie within $x < 0.4$ where there are also low driving gradients, R/L_{T_e} and R/L_{T_i}.

In addition, the entire data set is approximately split in half between stable and unstable regimes, indicating that it should adequately cover regions of the input parameter space containing the instability thresholds. It is important that the NN surrogate model accurately determines these locations in order to provide good predictions in integrated modelling [4]. Uncertainty quantification of the input parameters will be carried out in a future step, and the data sets expanded through variations of the various gradient inputs within the uncertainties determined by the GPR fits. This expanded data set will be employed for the final NN regression.

Initial neural networks

By using pre-optimised training settings [4], a committee of 10 individual NNs were trained using the experimentally-derived training set, without expansion based on GPR uncertainties as a first trial. Figure 3 shows the comparison of the committee against the previous 10D NN. The prediction variance of the committee network provides a method of visualising the training set density of the non-regular data set, and thus allowing direct comparisons of the performance of the 15D NN to previous NNs. By comparing the NNs where the prediction variance is low, it can be seen that the 15D NN accurately reproduces the original model and is comparable to the 10D NN. This is highly encouraging for the ongoing progress in developing a JET-specific QuaLiKiz-15D neural-network surrogate. Furthermore, NN outputs with high variance is a robust way to identify sparse regions of the training set during integrated modelling, providing an in-situ measure of the trustworthiness of a given NN transport model prediction.

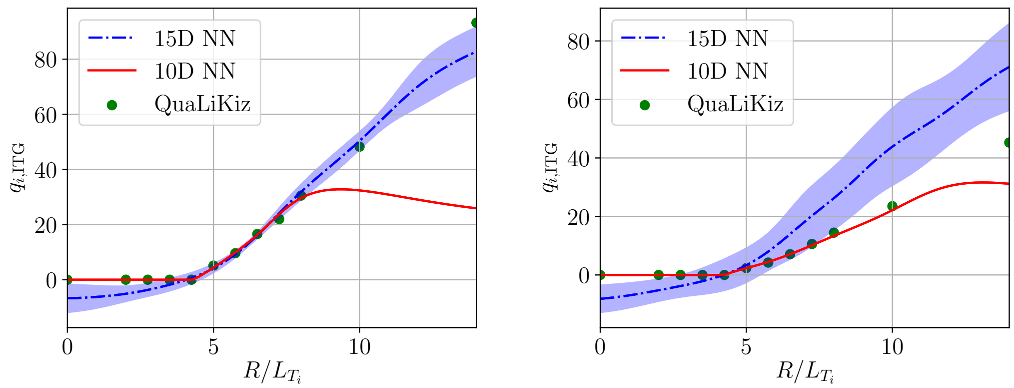

Figure 3: Comparison of initial 15D NN (blue line) with previous 10D NN (red line), for a region with high (right) and low data density (left). The other parameters for specifying the high data density plot are: $x = 0.57$, $R/L_{n_i} = R/L_{n_{\mathrm{imp,light}}} = R/L_{n_e} = 0.5$, $R/L_{T_e} = 6.5$, $\log(\nu^*) = -0.456$, $q = 2.5$, $\hat{s} = 0.7$, $Z_{\mathrm{eff}} = 1.3$, $T_i/T_e = 1$, $M_{\mathrm{tor}} = 0$, and $R/L_{u_{\mathrm{tor}}} = 0$. Flux, q, in GyroBohm units.

Conclusions

A 15D training set of $\sim 10^5$ individual points for the training of a NN surrogate model of QuaLiKiz was successfully constructed. By sampling the profiles fitted using the GPR algorithm on experimental data, the data set remains within an experimentally relevant parameter space. Preliminary NNs generated with this reduced data set are in good agreement with the base model and with previous NNs in regions of parameter space where the current data set density is sufficiently high. In order to increase the data set density further to improve the NN accuracy, these gradient quantities of the extracted data points will be expanded according to their uncertainties provided by the fitting routine.

Acknowledgements

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