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The instability prediction of non-resonant energetic particle modes based on machine learning algorithms

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Non-resonant energetic particle modes (EPMs) are commonly observed in tokamak experiments, and their excitation can disrupt plasma equilibrium, thereby reducing the confinement performance of the device[1] .Although traditional hybrid simulation methods can reveal the physical mechanisms of EPMs, they are often time-consuming and require high computational resources, which limits their application in practical experiments[2].

To address this issue, the present study is the first to propose a machine learning–based prediction model aimed at rapidly and accurately assessing the linear instability of non-resonant EPMs. We acquired a large amount of simulation data using the M3D-K global kinetic magnetohydrodynamic (MHD) code, and constructed the model by integrating methods such as data cleaning, feature selection, and cross-validation. The model takes eight different input feature variables, including the safety factor minimum (q_{min}), beam ion pressure fraction ($P_{ho}t/P_{total}$), particle injection energy (E_0) and pitch angle (Λ_0), among others, while the output variables are the growth rate (γ) and mode frequency (ω).

In this study, we compared four algorithms—decision tree regression, k-nearest neighbor regression, support vector regression, and multilayer perceptron. Through hyperparameter optimization, each model achieved prediction accuracies and R^2 values of approximately 0.9. Moreover, we systematically analyzed the impact of each input feature on the prediction of instability, thereby providing strong support for identifying the key driving factors behind the instability of non-resonant EPMs.

The machine learning model developed in this study can complete predictions on a standard computer in just 1 second, representing an efficiency improvement of more than four orders of magnitude compared to traditional simulation methods which require 12 hours per case. This achievement provides an efficient tool for real-time instability warning in tokamak experiments and lays a foundation for further expansion into more complex scenarios (such as nonlinear evolution prediction) by integrating methods such as deep learning and transfer learning. This work was supported by the National Key R&D Program of China under Contract No. 2024YFE03240300

References

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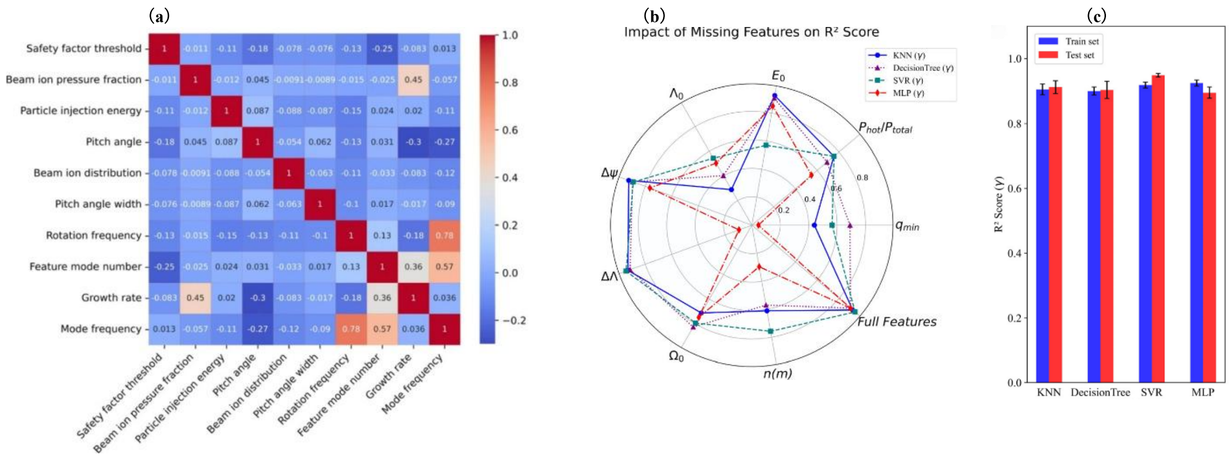

Figure 1. Figure 1(a) shows all pairwise attributes were analyzed for Pearson correlation, it can be observed that the most important correlation parameter varies for different output values, for γ, it is P_{hot}/P_{total} with PCC>0.4, while for ω, it is Ω_0 with PCC>0.7. Figure 1(b) shows the impact of absent characteristic variable on growth rate forecasting, it can be observed that when a characteristic variable is missing, all evaluation index converges, but significantly worse than the results predicted using the original data. Especially for MLP algorithms, the red dotted line in figure right shows that the evaluation index R2 is most obviously affected by the absence of characteristic. Figure 1(c) shows the evaluation results of employed models across 10 times sampling. In regard to evaluation metrics of growth, models achieve a good R2 value.