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Machine learning surrogate model for pedestal MHD stability

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Magnetohydrodynamics (MHD) simulations are key to assessing the H-mode pedestal stability in tokamak plasmas. EPED-like integrated pedestal prediction workflows, such as Europed [1], combine an equilibrium solver, such as HELENA [2], with an MHD stability solver, such as MISHKA [3], to find a stability-critical pedestal consistent with the applied transport constraint, such as the ballooning critical pedestal approach. These stability calculations constitute the main computational bottleneck in these workflows, making them a relevant target for surrogate modeling approaches, which is the focus of this work. A first version of this surrogate model, called KARHU [8], was developed using data generated by HELENA and MISHKA. As MISHKA is an ideal MHD stability solver, the present focus of the work is to extend to model to include resistive MHD features using CASTOR. The main experimental motivation for such extension is the fact that a significant fraction of the JET-ILW pedestal database is observed to be limited below the ideal peeling-ballooning MHD boundary [4, 5]. In these cases, modelling the peeling-ballooning stability boundary using resistive MHD has resulted in more accurate predictions, demonstrating the significance of resistivity in pedestal stability analysis [5]. The resistive MHD stability code CASTOR [6] was recently integrated into Europed and the first results determined resistivity to be a destabilizing factor in the pedestal [7]. As CASTOR is about twenty times slower than MISHKA, due to factor of four more equations to be solved, surrogating CASTOR is expected to be a key to enable large-scale resistive MHD stability analysis within Europed workflows.

For the initial KARHU model, a database containing 16 000 equilibria was created using E*nchanted-surrogates* [9, 10]. Seven machine parameters were randomly sampled, with additional assumptions introduced to reduce the dimensionality of the parameter space. For instance, no relative shifts between the density and the temperature profiles were considered. The ideal MHD stability of these equilibria was determined using MISHKA for toroidal mode numbers N_{tor} = 3, 5, 7, 10, 15 20, 30, 50. A convolutional neural network (CNN) model was trained on this database to predict the growth rate of the most unstable mode, achieving high predictive accuracy with a mean absolute percentage error (MAPE) below 1% on the test set.

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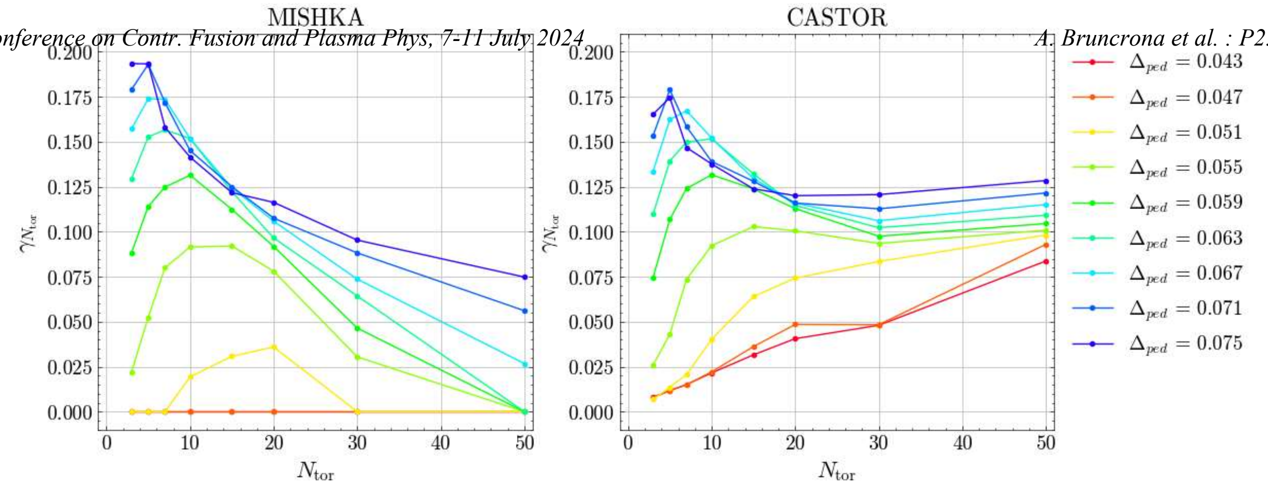
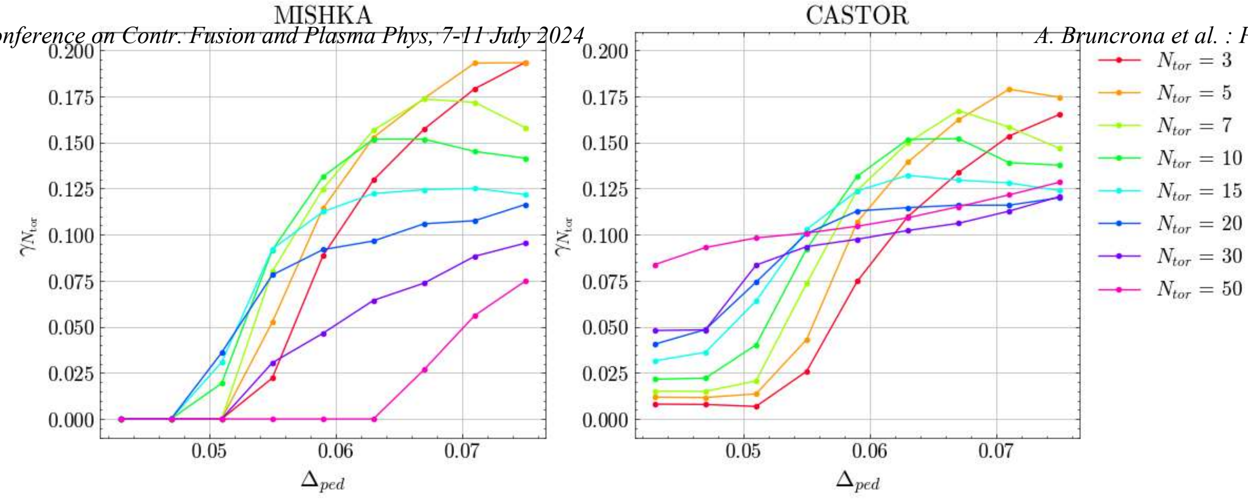


(a) (b)

Figure 1. The growth rate spectrums of ideal MHD (a) and the resistive MHD (b) for a pedestal width scan based on JET Pulse Number 84794.

In ideal MHD theory, the stability threshold can be defined as a fraction of the Alfvén frequency or compared to the diamagnetic frequency; if any growth rate of any mode exceeds this threshold, the plasma is considered unstable. Based on this criterion, the initial surrogate model KARHU, was trained to only predict the growth rate of the most unstable mode, γ_{max}. However, in resistive MHD, the stability threshold is less well-defined and may differ on a case-by-case basis. The full spectrum of growth rates, γ_{Ntor}, over the toroidal mode number N_{tor} needs to be analyzed to determine plasma stability, as the computed growth rates may begin to increase again after the actual peak due to computational artifacts or assumptions inherent to the resistive MHD formulation used by CASTOR. To demonstrate this, a width scan of JET Pulse Number 84794 was performed using HELENA for equilibrium reconstruction, and MISHKA and CASTOR for stability analysis (Fig. 1). This pulse was selected for demonstration since previous studies found that resistivity affects its MHD stability for low $N_{tor} \leq 20$[7]. The stability improves with decreasing pedestal width, Δ_{ped}, in both the ideal and the resistive cases. However, the equilibria that are ideal MHD stable ($\Delta_{ped} = 0.043$ and $\Delta_{ped} = 0.047$) and the equilibrium that is ideal MHD marginally stable ($\Delta_{ped} = 0.051$), are showing increasing resistive MHD growth rates, making them resistive MHD unstable (or marginally stable, depending on the stability threshold used). Also, in the ideal MHD case, the growth rate γ_{Ntor} increases with N_{tor} until the most unstable mode is reached, and then the growth rate decreases with increasing N_{tor} (Fig. 1a). Therefore, it can be sufficient to only predict the maximum growth rate γ_{max}. In the resistive case, after reaching the most unstable mode, the growth rate decreases slightly until it again starts to increase with N_{tor} and can exceed the previous peak (Fig. 1b). For this reason, it is not sufficient to only analyze the maximum growth rate for resistive modes.



(a) (b)

Figure 2. The ideal MHD (a) and resistive MHD (b) growth rates for each N_{tor} as a function of the pedestal width, as an example of eigenvalue tracing. Starting from the largest Δ_{ped} (representing the most unstable equilibrium), the eigenvalue for the next stability evaluation (decreasing Δ_{ped}, keeping N_{tor} constant) is computed using the current eigenvalue as initial guess.

To develop a surrogate model for predicting the resistive MHD stability, a dedicated database must be generated using CASTOR. On average, CASTOR is approximately twenty times slower than MISHKA due to it using eight variables in comparison to MISHKA's two [3]. Therefore, choosing a relevant domain for sampling is key. CASTOR is also more difficult to converge than MISHKA and typically requires more accurate initial guesses to successfully compute the eigenvalues. One strategy to address this challenge is called eigenvalue tracing (Fig. 2). This approach begins with having a highly unstable equilibrium, where the eigenvalues are relatively easy to solve, and progressively reducing the pedestal width, using the previously computed eigenvalue as the initial guess for the next equilibrium. This method significantly improved convergence when generating the pedestal width scan.

Although the initial KARHU surrogate model was trained on exclusively ideal MHD stability simulations, it is useful to assess its extrapolation ability on physically relevant regimes. The stability of the JPN 84794 width scan was therefore predicted using the KARHU surrogate model (Fig. 3), given that this pulse lies outside the domain of the original training data ($\Delta_{ped} > 0.065$, elongation $\kappa = 1.64$) and includes pedestal characteristics (relative shift) not accounted for in the initial surrogate model. The results showed limited agreement with MISHKA, which provides insight into the model's limitations and highlights the need for extending the training dataset.

To conclude, ideal and resistive stability analysis of JPN 84794 demonstrated the impact of resistivity and highlighted necessary improvements for both the surrogate model and the data generation process. Incorporating resistive MHD into the surrogate model requires training data generated by CASTOR, and the sampling must be extended to include relative shifts in

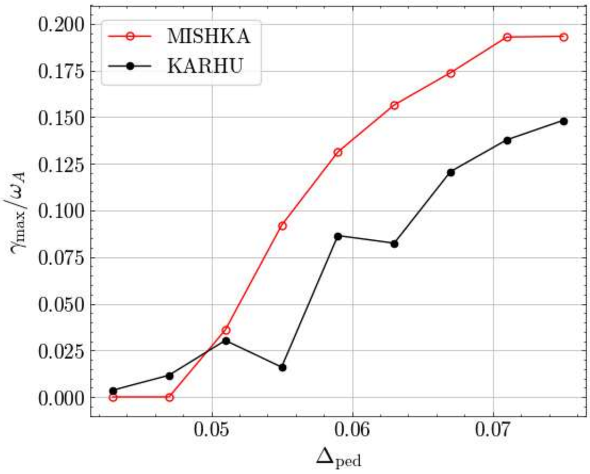


Figure 3. KARHU prediction compared to the MISHKA simulation for the growth rate of the most unstable mode of a pedestal width scan for JPN 84794, which falls outside the parameter space of the database used for training KARHU.

the pedestal profiles. A workflow for eigenvalue tracing also needs to be developed and implemented into E*nchanted-surrogates*. The machine learning model architecture must be restructured to predict the growth rate for each toroidal mode number, rather than only the maximum growth rate. These developments represent important steps toward building a more accurate and generalizable surrogate model for MHD stability analysis.

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