PFNN: Less data and better performance on disruption prediction via physics-informed deep learning

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Disruption prediction and mitigation is a crucial topic, especially for future large-scale tokamaks, due to disruption's concomitant harmful effects on the devices. Recent progresses have proved that deep neural network can accurately predict the coming disruptions by learning from history experimental data, which becomes a potential solution for the disruption prediction in future devices [1, 2]. This technique routine has also been proved in HL-2A tokamak, both in offline testing and online experiment [3, 4, 5]. However, a key issue about this technique routine is whether the deep learning model can be developed on future devices, since these devices can only tolerate a few disruptions and therefore can't provide much training data [6]. In this research, a predict-first neural network (PFNN) is developed in HL-2A. Two predict-first tasks are designed to embed physical knowledge into the neural network. Ablation experiments show that the embedded physical information significantly improve the algorithms' performance, especially when the training data is limited.

The first predict-first task is to let the neural network predict the evolution of electronic temperature (Te), electronic density (Ne) and horizontal displacement (Dh) according to the control target, control actuators and the plasma state. A preparatory neural network based on encoder-decoder framework [7] is trained on this task and three empirical equations are hidden in the design of the neural network. After the training, the neural network learns the three equations and can accurately predict the evolution of Te, Ne and Dh, as shown in figure 1. Then this preparatory neural network can be used as a feature extractor in the disruption prediction algorithm and use the three equations to promote the performance of disruption prediction.

The second predict-first task is to mask part of the experimental data and let the neural network restore them. Another preparatory neural network based on masked auto-encoder framework [8] is trained on this task. It can realistically reconstruct the masked parts according to the unmasked parts and the correlation between different input signals. This preparatory neural network can also be used as a feature extractor in the disruption prediction algorithm and use the correlation between different input signals to promote the performance of disruption prediction.

Ablation experiments show that the embedded physical information significantly improves the algorithms' performance. When the amount of training shots is limited to 1283 shots, the AUC (area under receiver-operator characteristic curve) of PFNN is about 4% higher than the ordinary one, as shown in figure 2. In general, PFNN, which is pretrained by predict-first tasks to learn physical information and then trained for disruption prediction in the second step, performs much better on disruption prediction when the amount of training data is limited. It can be a potential solution for future tokamaks' disruption prediction problem.

References

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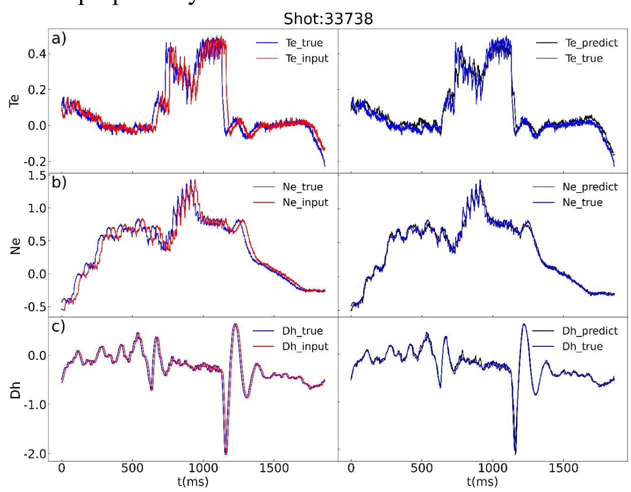

Figure 1. a), b) and c) are electron density, electron temperature and horizontal displacement, respectively. On the left is the comparison of algorithm inputs and target outputs, where an obvious delay of ΔT can be observed. Here ΔT is 30ms for Ne and Te, while it is 10ms for Dh. On the right is the comparison of predicted parameters and target outputs, they are much closer than the situation in the left subfigures.

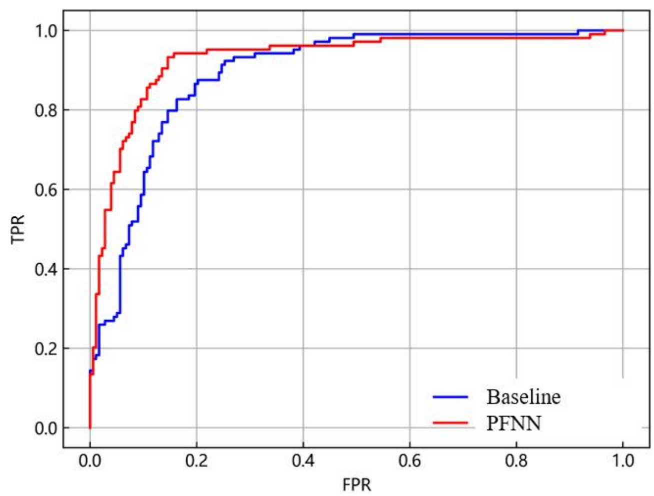

Figure 2. Comperison between the receiver-operator characteristic curves of baseline(red) and PFNN(blue) algorithms. Obviously PFNN performs better than the baseline algorithm, which is trained from scratch without the embedded physical knowledge.