DISRUPTION PREDICTION FOR FUTURE TOKAMAK REACTORS FROM DIFFERENT PERSPECTIVES AND WITH DIFFERENT METHODS

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1. INTRODUCTION

Accurate disruption prediction is one of the keys for tokamaks to be commercially viable reactors. Machine learning disruption predictors exhibit good performance on the machines they are trained on. However, future reactors cannot provide enough disruption data before they damage themselves [1-3]. Moreover, for future large scale experimental tokamak reactors, at different operation phases, they will have different goals, generate different data with different risks. The requirements on disruption prediction system are different. In this work, we designed different methods and strategies tailored to different operation phases. First we present an anomaly detection disruption predictor which can be deployed for the very first shot of a new machine. Then as the operation carried on, and more data are generated. We use this data to transfer a model trained with existing tokamaks to the new machine. Physics guided methods are introduced to minimizing the requirements on the data from the new machines. Then with disruption protections from the previous methods, we are able to safely operate the tokamak and generate even more data. From this point on just provides a simple trigger to DMS is not enough. We here present a time to disruption prediction model, which is able to give the approximate time to disruption. All the above can disruption prediction be given additional safety margin by disruption budget guided operation. This will ensure that the operation generates the best data for disruption prediction model training while posing the least danger to the machine.

2. ADAPTIVE ANOMALY DETECTION DISRUPTION FROM SCRATACH

When a new large tokamak start operation or start high performance operation, it does not have any data to train a disruption predictor or data from the previous stage is too different to train a high performance disruption prediction model. In this study, we present an adaptive anomaly detection method that uses existing experiment data to train an initial model [4, 5]. Then the model can be used from the very first shot of the new machine of the new phase. After each shot, the model can be adaptively retrained, to follow the evolution of the operation of the new machine. The highlight of this method is that the predictor is an anomaly detection model so it can be adaptively with every shot from the new machine even there are only non-disruption shots. However, it can be pre-trained with both disruption and non-disruption shots from the existing tokamaks [6].

3. PHYSICS GUIDED DEEP TRANSFERABLE DISRUPTION PREDICTOR

The previously introduced method although can provide basic protection to the machine, the performance is limited, as it could introduce higher false alarm rate than acceptable, once scientific experiment started. We introduced a physics guided deep transferable disruption predictor, which use deep transfer learning to transfer a model trained with past experiment data to the new machine with little data from the new machine [7]. To ensure the transfer performance, 2 physics guided mechanisms are added to the neural network and the training process. One is to add known disruption related limits into the loss function of the disruption classifier. The other forces the feature extractor to extract know disruption related physics features. This will make the model generalize better by guiding it with known disruption precursor physics patterns that have been proven on multiple tokamaks.

4. TIME TO DISRUPTION PREDICTION

As more and more data is generated during operation of the reactor. Just predicting if it need the DMS trigger is not enough. If time to disruption can be predicted it will be very useful since it will allow the PCS to take better action to safely terminate the shot other than firing the SPI. This will reduce the aftermath of DMS. In this research, again we used the anomaly detection model. The key characteristics of this model is it can very efficiently determine the onset of the disruption precursor without any human input. From this point onward we can train a supervised model to predict the approximate time to disruption.

5. DISRUPTION BUDGET GUIDED OPERATION

The previously mentioned method except the first one will require a different amount of disruption data to be trained although not many. But, for future reactors, just one unmitigated high performance disruption with runaway electron will pose catastrophic damage to the machine. However, not all disruptions are created equal. Some may have less damage to the machine. If we can have the total disruption damage to a safe level, then we can generate disruption data that covers as much disruption physics as possible without causing catastrophic consequence. Here we demonstrate that by carefully plane the shot, we can have enough data to train a disruption predictor that can be used for later risker operation phase.

6. CONCLUSION

Although the previously mentioned methods are still at a preliminary stage, they show that for different phases of ITER or similar large-scale experimental tokamaks, we need to focus on different requirements and use different techniques to address the disruption prediction problem. This is much simpler and more effective than one model for all phases strategy.

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