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Prediction of the plasma vertical instabilities using BERT

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Achieving and maintaining the conditions necessary for nuclear fusion is a complex and challenging task. One of the primary challenges faced is effectively suppressing plasma instabilities and disruptions. In this study, we employ Bidirectional Encoder Representations from Transformers (BERT) [1], a transformer-based model illustrated in Figure 1, to analyze a plasma discharge experiment. Our aim is to predict vertical plasma instability and identify the underlying phenomena responsible for these instabilities.

Since plasma with a D-shaped cross-section have demonstrated high performance, future tokamak devices will use elongated plasma [2]. However, more accurate vertical control and predictions will be necessary, as elongated plasma are vertically unstable and can cause disruptions in the plasma. To solve this problem, it is important to predict plasma vertical instability to control it safely. In order to address this complex problem, we utilized machine learning techniques, specifically neural networks and deep learning algorithms, to develop predictive models that can predict plasma vertical instability. The recent works have shown the effectiveness of using machine learning approaches based on experimental data for predicting plasma disruption prediction [3] and controlling the plasma shape [4]. The recurrent neural network (RNN) based models such as Long Short-Term Memory have been conventionally used to predict plasma disruptions using time-series data.

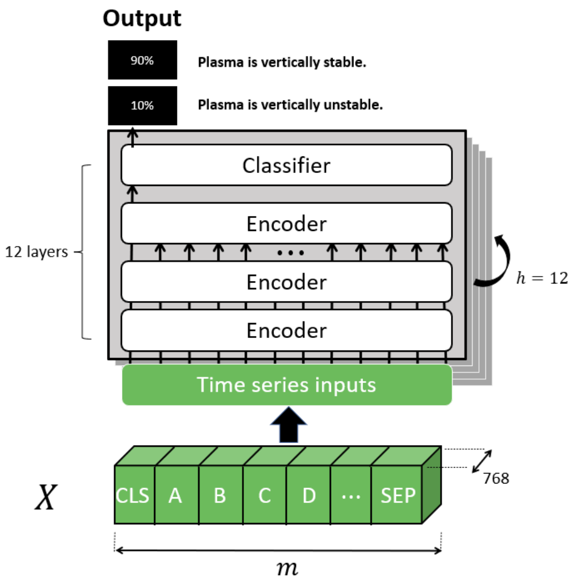

Figure 1. The structure of predictor of plasma vertical position. Arrows represent flows of a input data. Given an input length of m, and with h representing the head, let X denote the input. The encoder comprises a self-attention layer and a feedforward neural network (FFNN). By leveraging BERT's token, segment, and position embeddings, the model can generate dynamic word representations, enabling exceptional performance across a wide range of natural language processing tasks.

Transformer-based models such as Generative Pre-trained Transformer 3 (used for ChatGPT) have been utilized for tasks like time series prediction, language translation, and search engine functions. These models have achieved higher performance compared to conventional RNN-based and convolutional neural network (CNN) based models. The transformer's drawback of needing substantial amounts of time and tremendous data to train the model was a big problem. However, this issue has been solved recently using transfer learning, which enables efficient training of the model with small amounts of data by utilizing pre-trained weights from a larger dataset, thereby reducing the required computing resources.

The objective of this study is to identify the precursors and correlations of the observed and controlled parameters, and to forecast plasma instabilities within the near future, with a focus on predicting 0.01 seconds ahead. To achieve this goal, we used measured data of Kyushu University Experiment with Steady-state Spherical Tokamak (QUEST) [5]at three different points in time whose interval is 0.002 seconds. The relationships between the parameters related to plasma vertical displacement were analyzed, and we can predict the plasma vertical instability. This result serves as the basis for developing a predictive model that is capable of forecasting the plasma instabilities with high accuracy, up to 0.01 seconds into the future. We can also interpret the precursors and correlations of the parameters using BERT.

References

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