A machine-learning-based tool for last closed magnetic flux surface reconstruction on tokamak

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Abstract. Nuclear fusion power created by tokamak devices holds one of the most promising ways as a sustainable source of clean energy. One main challenge research field of tokamak is to predict the last closed magnetic flux surface (LCFS) determined by the interaction of the actuator coils and the internal tokamak plasma. This work requires high-dimensional, high-frequency, high-fidelity, real-time tools, further complicated by the wide range of actuator coils input interact with internal tokamak plasma states. In this work, we present a new machine learning model for reconstructing the LCFS from the Experimental Advanced Superconducting Tokamak (EAST) that learns automatically from the experimental data of EAST. This architecture can check the control strategy design and integrate it with the tokamak control system for real-time magnetic prediction. In the real-time modeling test, our approach achieves over 99% average similarity in LCFS reconstruction of the entire discharge process. In the offline magnetic reconstruction, our approach reaches over 93% average similarity.

Keywords: time series, magnetic reconstruction, tokamak Submitted to: Nature Communications
1. Introduction

Thermonuclear fusion power is one of the ideal forms of clean and sustainable energy that has the potential to meet our future energy needs while having inherently secure and deployable in densely populated cities. A tokamak is a leading magnetic confinement fusion device for generating controlled thermonuclear fusion power. One core research of tokamak is controlling strategy development for magnetic field profile, which is a complicated problem since the magnetic field is determined by the interaction of complex, sometimes unpredictable plasma states and a wide range of actuator inputs. Therefore, a high-precision and rapid magnetic field reconstruction [1–3] tool for developing a magnetic control strategy is urgently needed. The conventional approach to this time-varying, non-linear, multiple physical quantities magnetic field reconstruction problem is to solve an inverse problem to per-compute a set of actuator coil (poloidal field coils typically) currents and voltages [3–5]. Then, using a real-time estimate of the tokamak plasma equilibrium from a simulation code [6] modulates the actuator coil voltage. Although these physical simulation codes are usually effective, they require substantial physicist effort, design, and expertise to re-develop a model whenever the tokamak magnetic configuration is changed. A new approach to the estimator is made possible by using deep learning to generate high-precision, high-fidelity and rapid magnetic field estimation results. Complete tokamak proposal estimation is another critical problem to solve. The typical method is “Integrated Modeling” [7], and this approach runs slow. For instance, a few seconds’ discharge process generally take hours to days of computation. Moreover, it is also complicated to build due to the integration of many complicated physical processes. A high-precision and rapid magnetic field estimator based on experimental data-driven integrated with the other 0-D discharge proposal estimation methods [8] to create a complete and fast experimental discharge proposal estimation of a tokamak is also a good alternative.

Various works based on deep learning have been employed in magnetic confinement fusion research to solve a variety of problems recently years, including disruption prediction [9–15], electron temperature profile estimation [16], surrogate model [17–19], plasma tomography [20], radiated power estimation [21], discharge estimation [8, 22], identifying instabilities [23], neutral beam effects estimation [24], classifying confinement regimes [25], determination of scaling laws [26, 27], filament detection [28], coil current prediction with the heat load pattern [29], equilibrium reconstruction [16, 30–34], and equilibrium solver [35], control plasma [36–41], physic-informed machine learning [42], reinforcement learning-informed magnetic field control [3]. The reinforcement learning for magnetic field control work has a different target from our work. That work wants to design a magnetic field profile controller for tokamak discharge that can be used on the flat-top phase. The conventional controller should take it over in the ramp-up and ramp-down phases. There are two general machine learning models to deal with the sequence problem, the RNN [43] and its variants [44], and the Transformer [45] model based on the attention mechanism and its variants.

Modeling the entire tokamak discharge process using machine learning is a challenge, with current tokamak discharge times reaching the order of thousands of seconds [46] and sequence lengths exceeding $1 \times 10^6$ if the sampling rate is at $1kHz$. There are two general machine learning models to deal with the sequence problem, the RNN [43] and its variants, and the Transformer [45] model based on the attention mechanism and its variants. For the traditional RNN algorithm, train and inference time of the long sequence will be long. Since RNN is a sequential computation algorithm, the computation is difficult to reach a high parallelism. Moreover, for long sequences long time dependencies are easily lost, using RNN to model the long time series modeling problem is still an outstanding challenge. In case of transformer model based self-attention mechanism, it is
difficult to use it compute long sequence because its computational complexity is $O(n^2d)$, where $n$ is the sequence length. In practice, when the sequence length is over 1000, the train and inference time of transformer is become a bit unacceptable.

In this paper, our work reports two 1d shifting window transformer models, a real-time version and an offline version that can use on long time series in which computational complexity is linearly proportional to the sequence length $n$. Moreover, these models can be efficient from high parallelism since these models are based on the attention mechanism and discard the sequential algorithm. We built the models using experimental data-driven method. These models can use for the tokamak entire discharge process, from the ramp-up flat top to ramp-down phases. The models do not directly control the tokamak magnetic field but provide a highly accurate estimator of the magnetic field. The real-time model can be integrated with the tokamak’s real-time magnetic control system to assist the high-precision magnetic control by predicting the next step magnetic field. The offline model can be used to develop plasma magnetic field control strategies. Moreover, the offline model can also provide complete predicted proposal results by coupling with zero-dimensional discharge modeling methods [8]. For the real-time version model, the average similarity is over 99%, and the inference time is 0.7 ms (<1 ms in accordance with the control system requirements). For the offline version model, the average similarity is over 93%, and the inference time is ~0.22 s for sequence length $1 \times 10^6$.

In practical, according to the principle of magnetic field control [2], the machine learning model data set consists of the magnetic surface probes, in-vessel current, poloidal field coils, plasma current reference, shape reference, and flux loop data.

Our contributions are summarized as follows:
(i) We propose a generalized 1d shifting window transformer architecture that can compute long time series.
(ii) One of the models can be integrated into tokamak control for real-time estimating of the magnetic field in advance.
(iii) One of the models can also be combined with a 0-dimensional proposal validation model to give a complete prediction for experimental proposal results.
(iv) The validity of the proposed models is demonstrated using a practical data set.

2. Results and discussion

In this section, we use the similarity and MSE loss to quantitative measures of the magnetic field reconstruction accuracy.

$$S(x, y) = \max \left( \frac{\sum (x - \bar{x})(y - \bar{y})}{\sqrt{\sum (x - \bar{x})^2 \sum (y - \bar{y})^2}}, 0 \right),$$  \hspace{1cm} (1)

$$\text{MSE}(x, y) = \frac{1}{n} \sum_{i=1}^{n} (x_i - y_i)^2,$$

where $x$ is experimental data, $y$ is modeling result, $\bar{x}$, $\bar{y}$ are the means of the vector $x$ and vector $y$, $x_i$, $y_i$ are the point values of the vector $x$, $y$. The MSE is the mean ($\frac{1}{n} \sum_{i=1}^{n}$) of the squares of the errors $(x_i - y_i)^2$. MSE is easily affected by the outlier but it can more accurately measure the difference of values. Similarity measures tendency of two curve but it cannot measure the difference in value.
A machine-learning-based tool for last closed magnetic flux surface reconstruction on tokamak

Figure 1. Representation of the components of our machine learning model design and usage. a, The conventional controller working loop. The controller measurements difference between targets and the magnetic probe measurement values at the current time. According to the difference, the controller sends actions to the actuator coils. b, Depiction of the learning loop. The learner reads the measurements and targets from the HDF5 data store, and then computes the loss between the predicted magnetic field and the target magnetic field. Finally, using the loss as the criterion to train the learner. c, The online usage for the tokamak control. Our model can predict the tokamak outermost magnetic, the controller reads the estimation to generate the next control action sent to magnetic coils.

We trained, validated, and tested two version models on the dataset during the 2016-2020 EAST campaigns and the discharge shot number in the range #52804-88283 [47–49] and the input and output signals can be found in section 3.3.

2.1. Offline model results

Figure 2 shows that our offline version model predicted the last closed flux surface (LCFS). The discharge time of this shot is longer than 70s, so the sequence length is greater than $7 \times 10^4$, which is a typical long sequence modeling problem. The LCFS shown in the figure is generated from the physical equilibrium reconstruction code EFIT [50–52] by inputting the model predicted outputs into EFIT. The equilibrium reconstruction is another main task of tokamak research, and we do not discuss details in this paper. Figure 2 shows the model has wholly reconstructed LCFS not only flat-top phase but also ramp-up and ramp-down phases. The model reconstructs the tokamak start-up “cycle” magnetic shape to a single null shape and finally to a shut-down “cycle” shape. Our model can predict the entire discharge process.
Figure 2. Shot #73678 offline magnetic reconstruction. The LCFS was generated from EFIT. The solid blue lines are the target LCFS the red “star” markers are predicted LCFS.
The average similarity is 0.932

![Graph showing similarity distribution](image)

**Figure 3.** Similarity distribution of offline model predicted results on the test set.
The test set (see section 3.3) is in shot range #82651-88283 and some long-time shots.

The similarity in the test set is shown in figure 3. The offline model average similarity in the test set is 93.2%, and the similarity is concentrated at around 95%. The test set of this work is experiments in shot range #82651-88283 and some very long time experiments (see details on section 3.3). The similarity is defined on raw signal data instead of the reconstructed LCFS. We checked all experiments with similarity less than 0.85, and got a total of 98 shots. Among them, 89 are disruption shots, and 9 are normal shots. The offline model cannot predict tokamak disruption shots probably because the disruption has some random effects on the magnetic field that are not cover in input signals. The 9 normal shots (0.5% of the test set) are not well estimated, probably due to inherent limitations in the model, or inaccurate measurement of PF coils.

### 2.2. Real-time model results

The real-time model’s input and inference time requirements differ from the offline model’s input and inference time requirements. (discussed in detail in section 3.2). Figure 4 shows the reconstruction results of the real-time version model for shot #73678. For the real-time version of the model, the actual measurement data of the magnetic field probe at the previous step is fed as input to simulate the actual tokamak control feedback process.

The similarity of the real-time model in the test set is shown in figure 5, which is the same test set as the offline model.
Figure 4. Shot #73678 real-time magnetic reconstruction. The LCFS was generated by the same method with offline magnetic reconstruction. The solid blue lines are the target LCFS and the red “star” markers are predicted LCFS.
Figure 5. Similarity distribution of real-time model predicted results on the test set.
The test set for the real-time model and the offline model are the same.

Although there is almost no difference between the modeling results of shot 73678 in figure 2 and figure 4, comparing figure 3 and figure 5, it can be found that the real-time model results are a bit better than the offline model results. The possible reason is that the plasma magnetic field is not a rapidly changing process, and the actual system output information is a good guide to the current output. However, the offline model is not able to know the actual tokamak output, so even if bigger models are used for the offline task, the offline model results cannot be better than the real-time model results.

3. Method

3.1. Related work

The outermost magnetic field reconstruction has two research two paradigms: physics-driven and data-driven approaches.

Physics-driven approaches in magnetic field reconstruction have been studied for the last decades. They reconstruct physical high-dimensional reality from the bottom up and then reduce them to the low-dimensional physical process. By integrating the different physical processes, simulation codes have developed. A series of simulation codes based on tokamak physics have been developed. Such as Equilibrium Fitting (EFIT)[50–52], LIUQE [53], RAPTOR [54]. These codes must be recalibrated or redeveloped whenever the target plasma configuration or device changes.
Table 1. MLP, RNN, Transformer, Shifting window transformer comparison

| Model Type            | Computational complexity | Sequential operation | Maximum path length |
|-----------------------|-------------------------|----------------------|---------------------|
| MLP                   | $O(knd^2)$              | $O(1)$               | $O(n/k)$            |
| RNN                   | $O(nd^2)$               | $O(n)$               | $O(n)$              |
| Transformer           | $O(n^2d)$               | $O(1)$               | $O(1)$              |
| 1D Shifting Window Transformer | $O(w^2nd)$           | $O(1)$               | $O(n/w)$            |

Data-driven approaches discover the relationship between low-dimensional quantities from a large amount of data and then construct approximate models of the nonlinear dynamical system [8]. In recent years, various data-driven methods have been adopted in the fusion community to solve different tasks. However, magnetic reconstruction is far behind other applications in the fusion community. To the best of our knowledge, only a few works have been R&D. One representative work is controlling magnetic through deep reinforcement learning [3].

Our model is different from the other works. It can validate experimental proposals or act as a tokamak magnetic shape predictor in existing tokamak feedback control systems. Compared to the model [3], firstly, our model does not require an existing physics code. Secondly, since we used typical regression training, our model is more efficient than the model based on reinforcement learning. Finally, our model can be used from tokamak discharge ramp-up to ramp-down phases, not only in the top-flat phase.

3.2. Machine learning Model

The general architecture of our machine learning models is shown in figure 6. Our architecture uses a customized one-dimensional shifting window attention mechanism inspired by the Swin transformer [55] to get dependency between inputs and outputs. We stack self-attentive blocks to build the machine learning model.

There are four main candidate models for modeling such long-time sequences, which are convolutional neural network (CNN), Recurrent neural network (RNN), Transformer, and our customized 1D shifting window attention transformer. In addition, some critical quantitative criteria should be noted for modeling tokamak magnetic probe data: computational complexity, number of sequential operations, and maximum path length [56]. From the table 1, shifting window attention have the approximate equal sequential operation and computational complexity as MLP. Generally, the attention mechanism can achieve superior performance to MLP in numerous sequence works, such as natural language processing [45, 57].

There should be some differences between the real-time and offline model-building strategies. The real-time model requires that the single-step inference is fast enough. That is, the one-step inference time of the model should be less than the response time required by the control system, and the actual system output of the previous step can be fed back as the model’s input. The model inference time should be less than 1ms required by the EAST magnetic control system. For a typical transformer model, single-step input is complex. If the preset control commands are modified, the whole sequence needs to be recalculated, which makes the inference time exceed the control system requirements. In our work, we let “window size” = 1, which makes our model calculate the attention only in the channel axis, and single-step input become easy; furthermore, the one-step inference time is $\sim 0.7ms$. For the offline model, the actual system output from the previous step should not
be fed back as input unless it is trained using the teaching force trick. The time requirement of the offline mode can be reduced, but it should generally be within one hour. Otherwise, the advantage of the machine learning model over the integrated modeling model will be diminished. If we use the teaching force, we have to recompute all the past sequences step-by-step, so the inference time of the entire sequence will be in the order of $1 \times 10^5$ s for the reason of the computational complexity. This paper’s offline model does not use the teaching force trick since the inference time requirement is shorter than one hour.
| Signal     | Physical meaning                  | Number of Channels | Meaning of channels |
|------------|-----------------------------------|--------------------|---------------------|
| Output     | Signals                          | 73                 |                     |
| BP         | Equilibrium magnetic probes      | 38                 | 35 magnetic probes data |
| FL         | Flux loops                       | 35                 | 38 flux loops data  |
| Input signals |                                   | 57                 |                     |
| Ref. $I_p$ | Reference of plasma current      | 1                  | Plasma current reference |
| IC1        | In-vessel coil no.1 current      | 1                  | In-vessel coil no.1 current |
| PF         | Poloidal field coils current     | 12                 | Poloidal field no.1-12 coil current |
| Ref. PF    | Nominal current of poloidal field coils | 12                  | Nominal current of poloidal field no.1-12 coil |
| Ref. Shape | Shape reference                  | 20                 | 11 groups of control points |

### 3.3. Dataset

In this paper, a total of 16609 shots of data with EAST discharge range between #56804-96915 were selected to construct the total dataset. The training set, validation set, and test set are divided in chronological order. The training set has 14732 shots, the validation set has 200 shots, and the test set has 1677 shots. In this experimental range, there are only 30 long discharge shots (discharge time >50s), of which 10 shots are included in the training set, and the remaining 20 shots are included in the test set. As shown in table 2, we have selected the reference of plasma current, the in-vessel current IC1, the poloidal field coils current, the reference of poloidal field coils, the shape reference as the input signal, and the output signal including all magnetic probe signals of the magnetic field. Since the in-vessel current IC1 could not be obtained in advance at the experimental proposal stage, the input signal of the offline model did not include IC1, and the output signal previous step data of the system was not input to the offline model for efficiency reasons. All data are sampled at the same sampling rate, 1kHz from the time zero to the end of the discharge, and the time axes of all signals are aligned. All data were saved to HDF5 files shot-by-shot, and for fast and robust training, each discharge experiment was saved as a separate HDF5 file, with 209GB of original data.

### 3.4. Model training

Before the model is trained, each signal’s mean, variance, and presence flag are calculated for each shot, and then the data is stored in a MongoDB database. Then the data is normalized for each shot and finally fed into the machine learning model for training. The inputs are different for the offline model and the real-time model. As analyzed 3.2, the real-time model input dimension is 130, which includes the system output at the previous step and the current IC1 signal. We can use
A machine-learning-based tool for last closed magnetic flux surface reconstruction on tokamak

Table 3. Our model Hyperparameters. Model architecture can be found in figure 6

| Hyperparameter     | Explanation | Best value of real-time model | Best value of offline model |
|--------------------|-------------|-------------------------------|-----------------------------|
| $\eta$             | Learning rate | $1 \times 10^{-4}$            | $1.5 \times 10^{-4}$        |
| Optimizer          | Optimizer type | SGD                           | SGD                         |
| Loss               | Loss function | MaskedMSELoss                 | MaskedMSELoss               |
| Epoch              | Number of epochs | 40                            | 35                          |
| Scheduler          | Scheduler type | OneCycle[60]                  | OneCycle                    |
| Window_size        | Window size   | 1                             | 12                          |
| C                  | Input Channel | 130                           | 56                          |
| E                  | Embedded dimension | 60                | 36                          |
| [D0, D1, D2, D3]   | Depth list for layers | [2,2,4,2]       | [2,2,4,2]                   |

The teaching force for training, and IC1 can be got on real-time experimental. The input dimension is 56 since the IC1 and the system output at the previous step are not used as the offline model’s input.

Both versions of the model use Centos OS executing on 8 P100 GPU cards. During the training of our model, we used a custom masked mean square error (MSE) loss function (MaskedMSELoss).

$$l(x, y) = L = \frac{\sum_{i=0}^{N} \{l_1, l_2, \ldots, l_N\}}{N}, (2)$$

$$l_i = \sum_{j=0}^{\text{len}} f_i \cdot (x_i^j - y_i^j)^2, (3)$$

where $x$ is batch experimental sequence data, $y$ is batch predicted sequence result, $x_i^j, y_i^j$ are the $j$th point values of the $i$th experimental sequence and predicted sequence. $f_i$ is a signals data existence vector of $i$th experimental sequence, $f_i$ equals to 1 when the sequence exists and 0 when it does not. $f_i$ is used to mask a signal that does not have original data. The $\sum_{j=0}^{\text{len}}$ is another mask for the invalid length of the sequence. This term prevent training on the zeros padding of the sequence. The use of existence masks and length masks can prevents models from being trained on sequences without actual target values and meaningless zeros padding tails, which can improve the accuracy and speed of training. In the training process, we used the bucketing algorithm [58] for training acceleration, and finally we used the Tree of Parzen Estimator algorithm [59] for the architectural hyperparameter search, and we also tried various optimizers and regulators, and finally obtained the optimal set of hyperparameters as shown in table 3.

4. Discussion

In the current work, we propose a one-dimensional shifting window Transformer model that can perform long sequences ($10^6$ sequence length for LCFS reconstruction), which reduces the computational complexity of the transformer model from being squarely related to the sequence length to being linearly related to the sequence length, and which can form a general sequence processing backbone network for real-time sequence modeling or offline sequence modeling. To be best of our knowledge, we have achieved the first data-driven modeling of LCFS of a tokamak from the ramp-up, flat-top to ramp-down phases. The inference time for the real-time modeling
is $\sim 0.7ms$ with an average similarity of $>99\%$, and the inference time for the offline modeling is $0.22s$ with an average similarity of $>93\%$.

From the machine learning point of view to the best of our knowledge, we are the first to propose an attention-based mechanism for modeling long sequences. From the point of view of tokamak physics research, we have achieved high precision and fast tokamak magnetic field modeling, which can be used for real-time tokamak magnetic field control and offline validation of tokamak’s experimental proposals. If integrated with the existing discharge modeling model [8], it can also support the development of the tokamak running scenario. In the future, we will realize a real connection with tokamak magnetic field control instead of testing in a tokamak magnetic field simulation environment. Further validation of the full proposal is also one of the directions for future work. Testing of 1D shifting window models in general areas of machine learning such as NLP is also one of the next directions of work.

5. Data availability

The data that supports the findings of this study belongs to the EAST team and is available from the corresponding author upon reasonable request.

6. Code availability

The model code is open-source and can be found in github https://github.com/chgwan/1DSwin. The other codes for model training, data acquisition, and generate figures belongs to EAST team and is available from the corresponding author upon reasonable request.

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