Discharge Modeling in EAST Using Bidirectional LSTM

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Outline

- Background
- Method
- Results
- Conclusions

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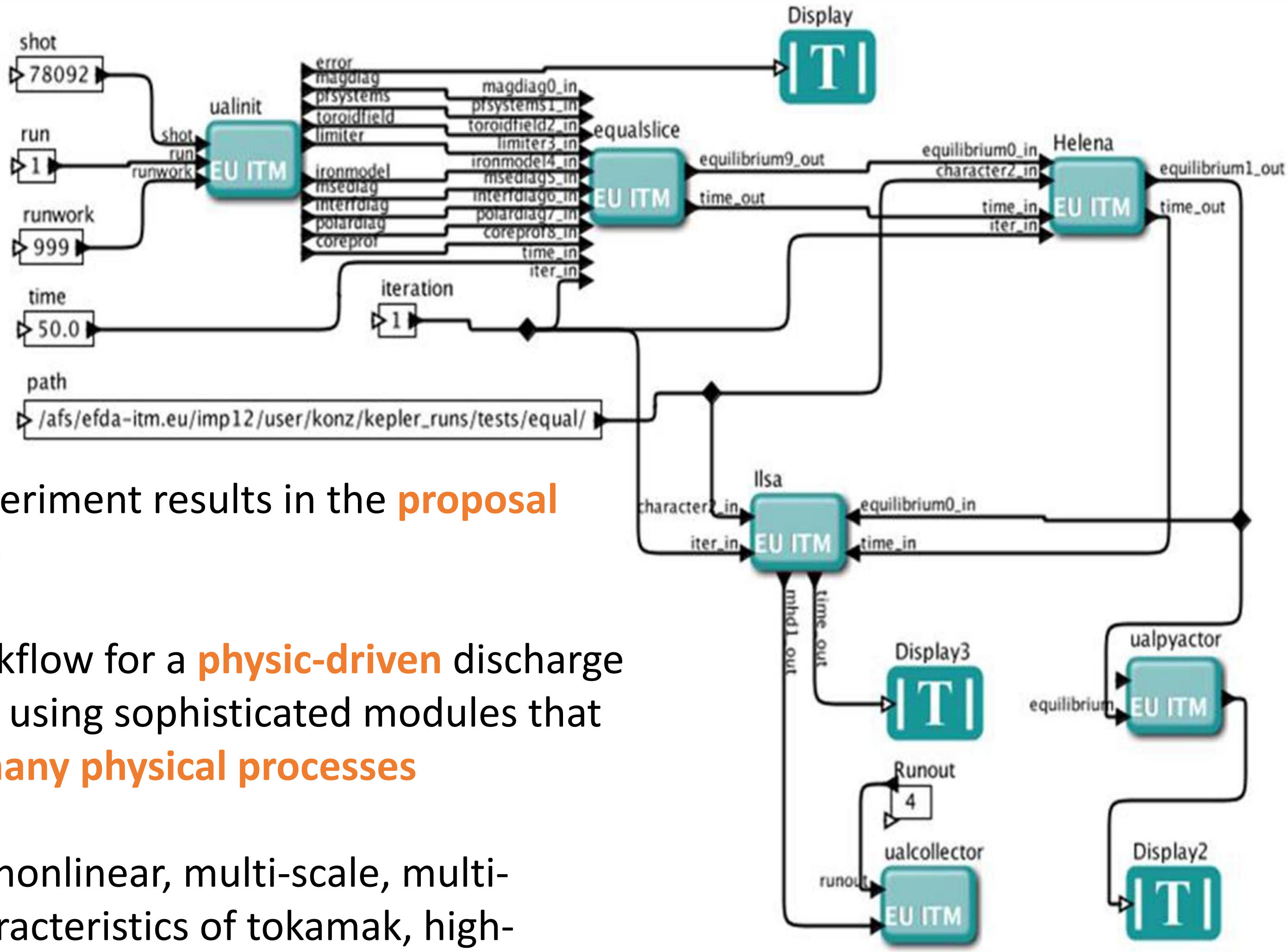
Discharge modeling



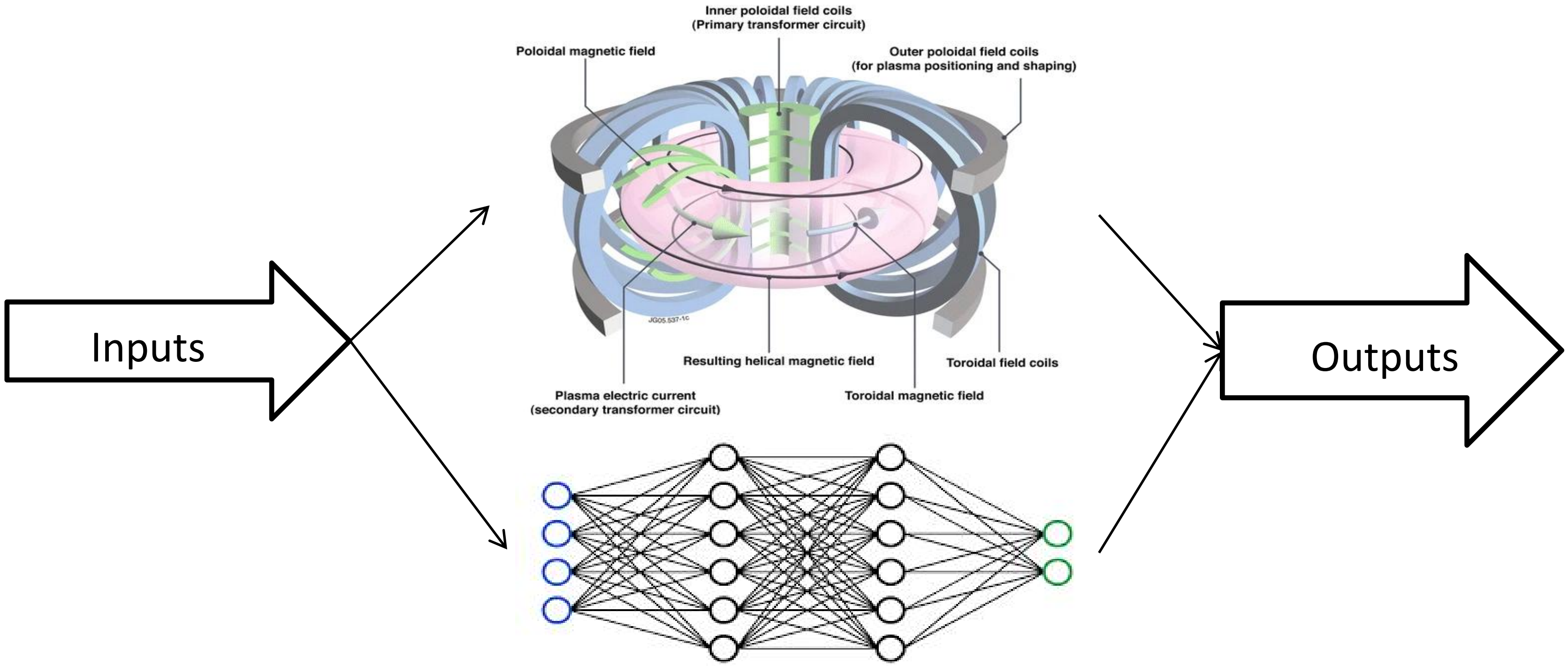
- Getting experiment results in the **proposal stage**

- Typical workflow for a **physic-driven** discharge modeling is using sophisticated modules that **integrate many physical processes**

- Due to the nonlinear, multi-scale, multi-physics characteristics of tokamak, high-fidelity discharge modeling is still a **great scientific challenge**

Wrokflow of integrate modeling by G.L. Falchetto et al 2014 Nucl. Fusion 54 043018

ML discharge modeling



- Divided the tokamak data into **three** categories: **actuator signals** (NBI, ICRH, etc), **diagnostic signals** (W_{mhd}, n_e, etc.), and **configuration parameters** (position of the poloidal magnetic field (PF) coils, etc.).
- The machine learning discharge modeling can be essentially reduced to a process of mapping **actuator** (input) signals to **diagnostic** (output) signals while the configuration parameters are unchanged.

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BiLSTM Framework

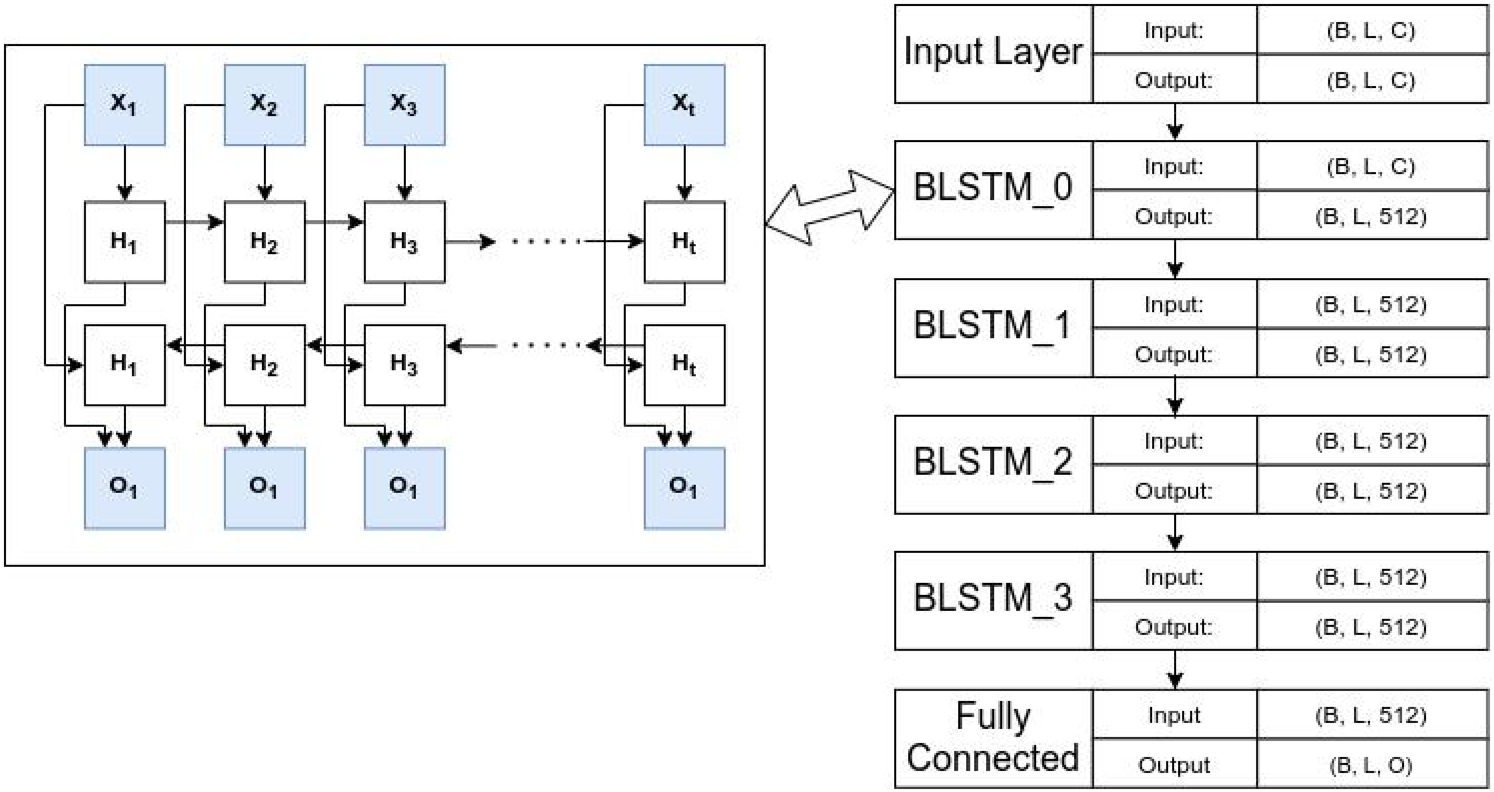

Fig 4. Architecture of BiLSTM

- Reason
  - Discharge modeling is a **offline** modeling task, so the **contextual information** is available and equal vital with past information during the experiment proposal stage
  - The pervious works only using **past** information

Signal selection

Signals	Physics meanings	Unit
Output Signals		
Act.I_p	Actual plasma current	A
n_e	Electron density	$10^{19}m^{-3}$
W_{mhd}	Plasma stored energy	J
V_{loop}	Loop voltage	V
β_n	Normalized beta	dimensionless
β_t	Toroidal beta	dimensionless
β_p	Beta poloidal	dimensionless
κ	Elongation at plasma boundary	dimensionless
l_i	Internal inductance	dimensionless
q_0	q at magnetic axis	dimensionless
q_{95}	q at 95% flux surface	dimensionless
Feedback Signal		
sycic1	In-vessel coil no.1 current	A
Input Signals		
Ref.I_p	Reference plasma current	A
PF	Current of Poloidal field (PF) coils	A
B_{t0}	Toroidal magnetic field	T
LHW	Power of Lower Hybrid Wave Current Drive and Heating System	kW
NBI	Neutral Beam Injection System	Raw signal
ICRH	Ion Cyclotron Resonance Heating System	Raw signal
ECRH/ ECCD	Electron Cyclotron Resonance Heating/Current Drive System	Raw signal
GPS	Gas Puffing System	Raw signal
SMBI	Supersonic Molecular Beam Injection	Raw signal
PIS	Pellet Injection System	Raw signal
Ref. Shape	Shape reference	Raw signal

- Output signals
  - Eleven key diagnostic signals can be obtained **stably**.
- **Feedback signal**
  - According to the magnetic control logic diagram, the in-vessel coil (IC) must be included.
- Input signals
  - Auxiliary heating system, shape reference, magnetic system, etc.

Modeling Procedure

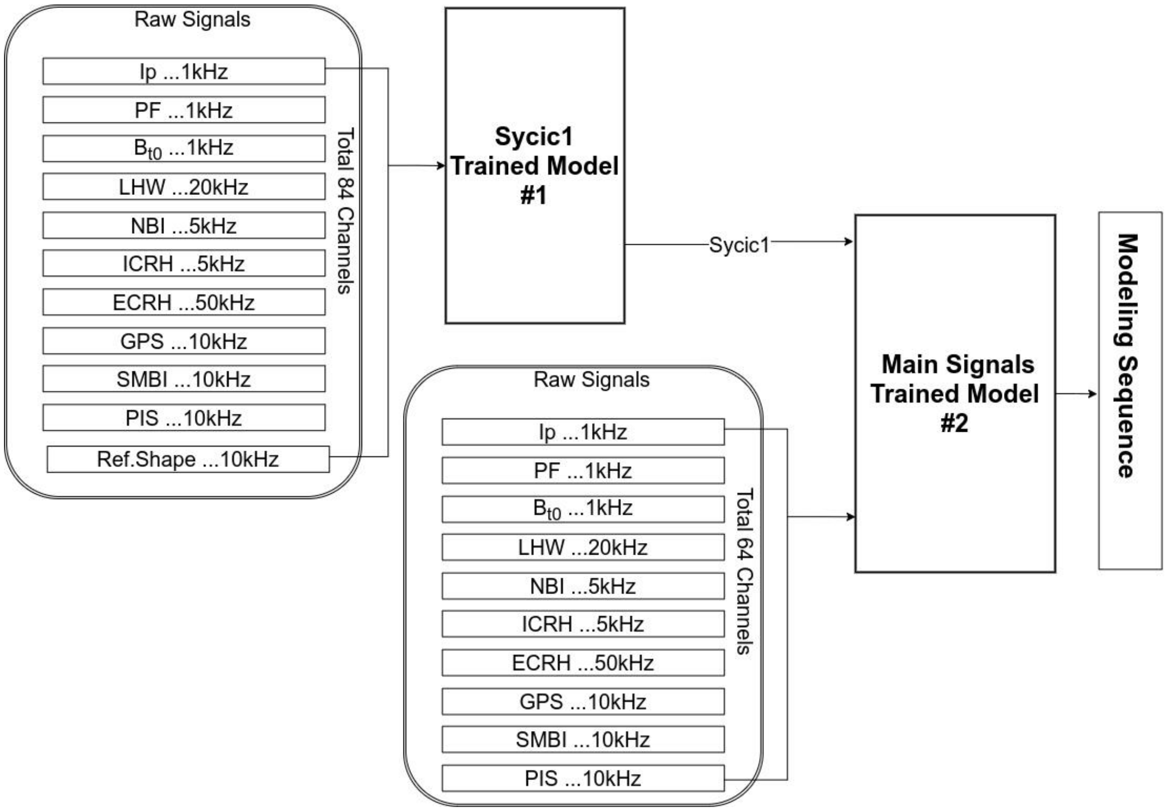

Fig 2. Workflow of the inference

- Feedback signal
  - ➢ Modeling “**sycic1**” first and then modeling main diagnostic signals.

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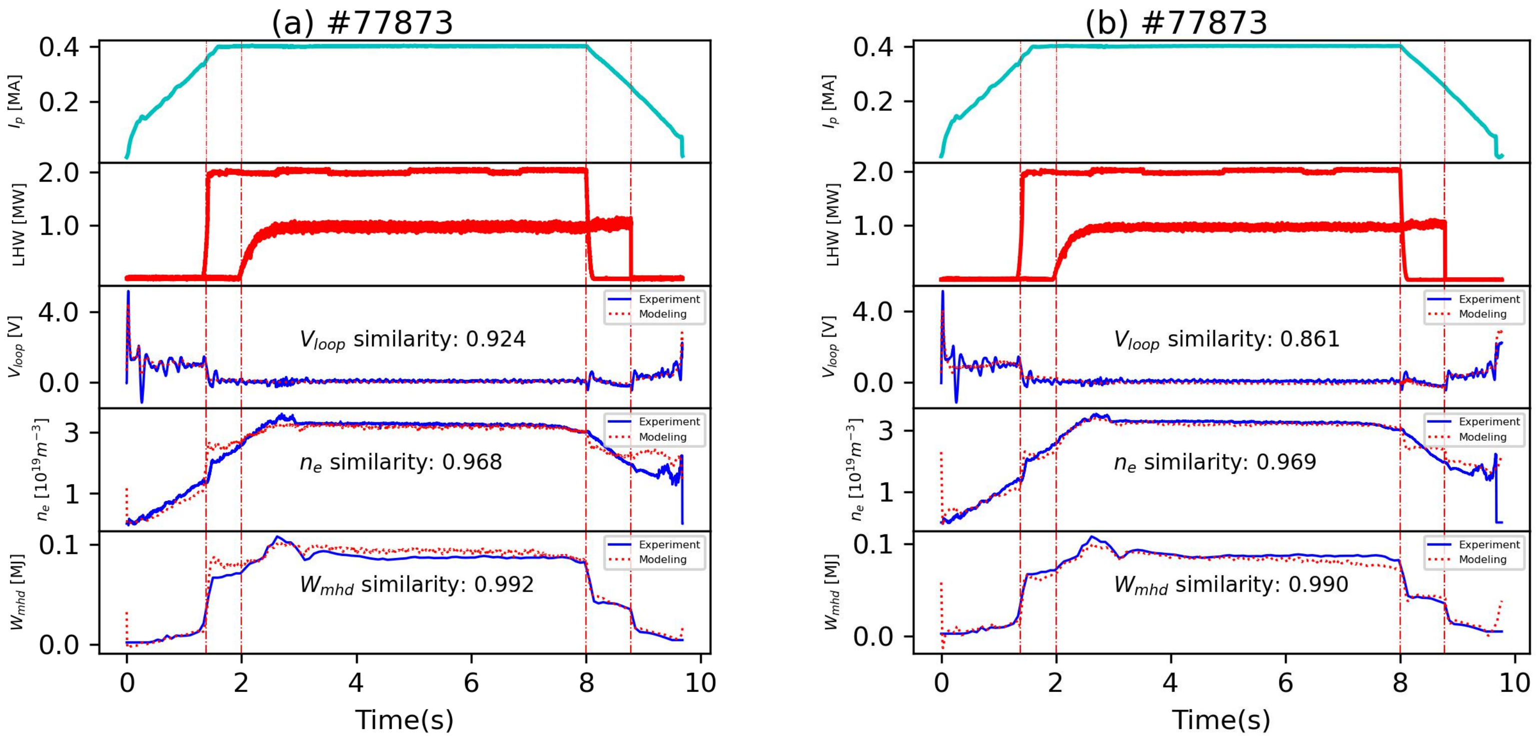
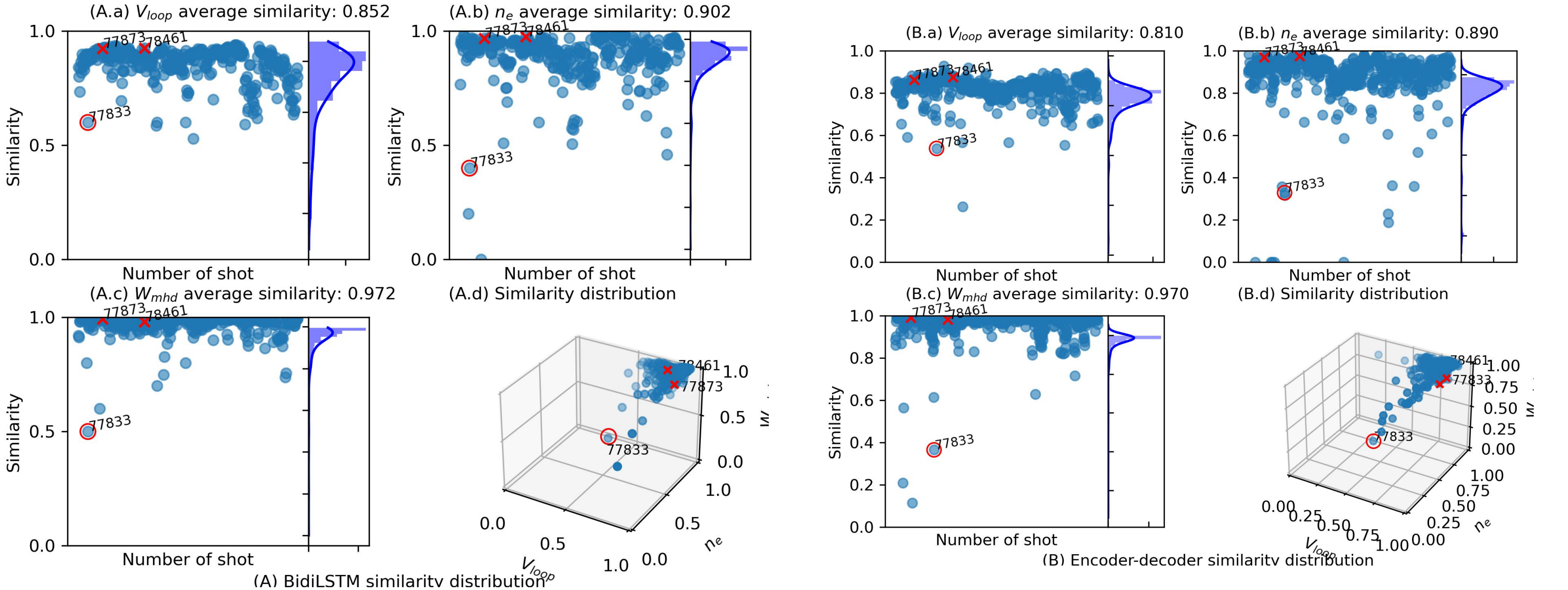
Comparison-Typical shot



The results of bidirectional LSTM (a) and past information model (b)

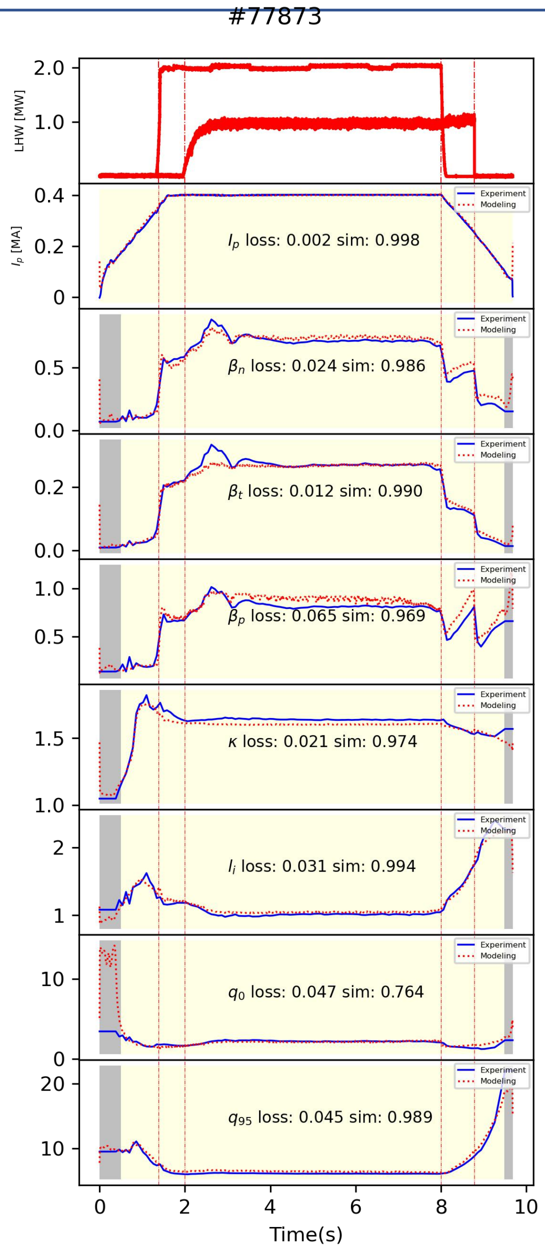
- The comparison shows the bidirectional LSTM can get better modeling results of V_{loop} than model only using the past information even though **not** using adaptive resampling and actual plasma current.
- The BiLSTM is more sensitive to the rising edges of the auxiliary heating signals than past information model.

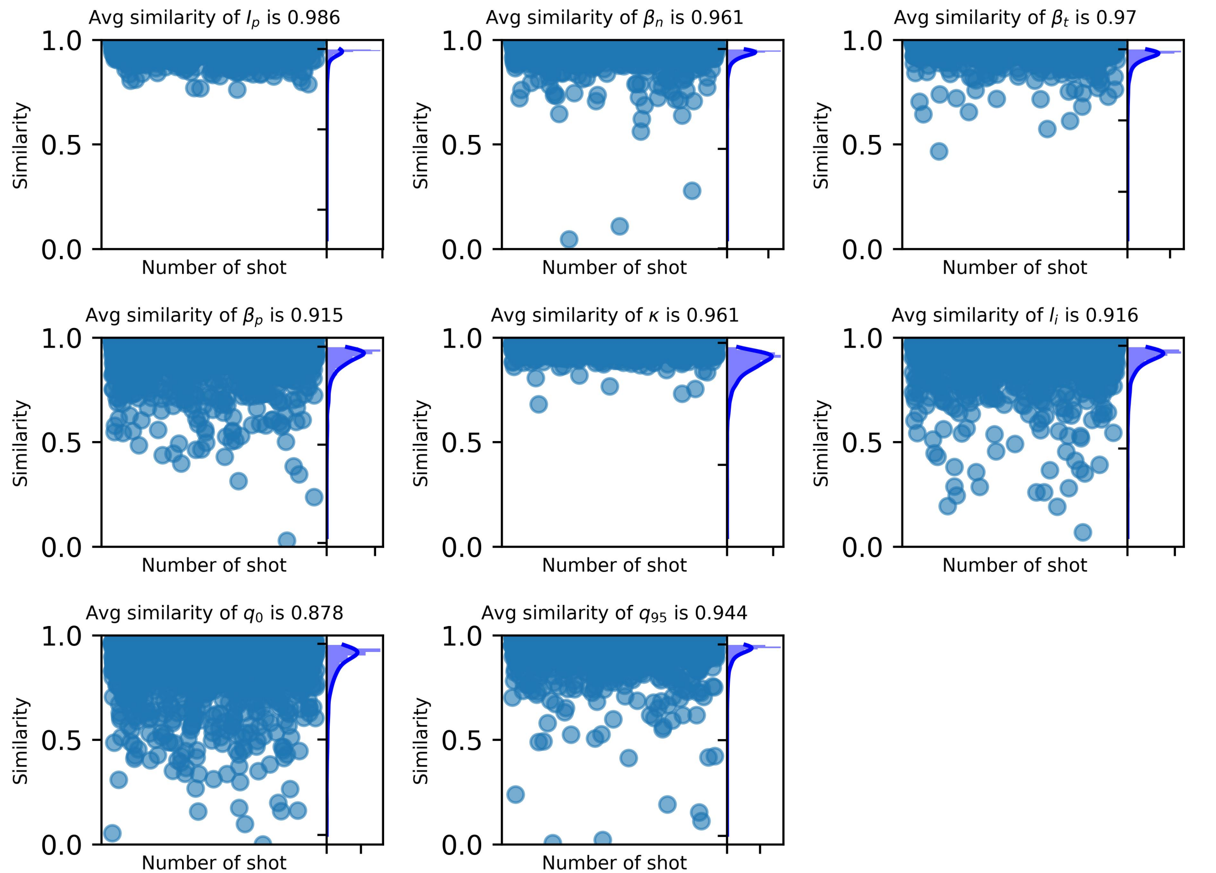
Comparison-Distribution



- The similarity of electron density n_e and loop voltage V_{loop} is improved by **~1%**, and **~5%**.
- The W_{mhd} is good enough only using the bidirectional LSTM is not work. We think the reason is the **random variation** of input signals and W_{mhd} itself.

Other singles





- Except for q_0, the average similarity of other key signals is greater than 90%. And the similarity distribution is concentrated above 90%.
- The reason for the low average similarity of q_0 is that its value is around zero.

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Conclusions

- Providing reference in the experimental **proposal stage**.

  - The electron density n_e, store energy W_{mhd}, loop voltage V_{loop}, actual plasma current I_p, normalized beta β_n, toroidal beta β_t, beta poloidal β_p, elongation at plasma boundary κ, internal inductance l_i, q at magnetic axis q_0, and q at 95% flux surface q_{95} are predicted in the proposal stage.

  - Except V_{loop} other signals can be considered well modeling.

  - 1-D profile modeling in the next step

- Providing **accuracy values of whole discharge process** compared to other models.
- Limitations

  - Temporarily unable to predict a discharge curve in real time.
  - Temporarily have not cross-tokamak capacity. (**device dependant**)
  - Temporarily unable to achieve dimensionless.

https://chgwan.github.io/DataBase/Wan_2021_IAEA_report.pdf
https://chgwan.github.io/DataBase/draft_Proof_hi.pdf

Thank You!