Design of a PID controller for the pedestal top electron density at KSTAR

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Introduction

1. Electron density profile can be reconstructed using five channels of two-colored interferometer (TCI) [1].
2. The reconstruction algorithm can be accelerated by using a neural network, enabling real-time density profile control in KSTAR.

1. Electron density profile reconstruction model

(a) Edge model: $a_1\left[\gamma+\frac{1-\gamma}{2}\left(1-\frac{\tanh(\frac{\psi-\psi_m}{\Delta/2})}{\tanh(1)}\right)\right]$

(b) Core model: $a_2\left|1-\left(\frac{\psi}{\psi_t}\right)^{a_3}\right|^{a_4}$

ψ	: Normalized poloidal flux function
ψ_m	: Position of the middle of pedestal $(\psi_m = 1-\Delta/2)$
Δ	: Pedestal width
a_1	: Plasma density at the pedestal top
γ	: The ratio of electron density between pedestal top and LCFS

ψ_t	: Position of the pedestal top $(\psi_t = 1-\Delta)$
a_2	: The difference of the plasma density between axis and pedestal top
a_3	: Fitting coefficient in the core region
a_4	: Fitting coefficient in the core region

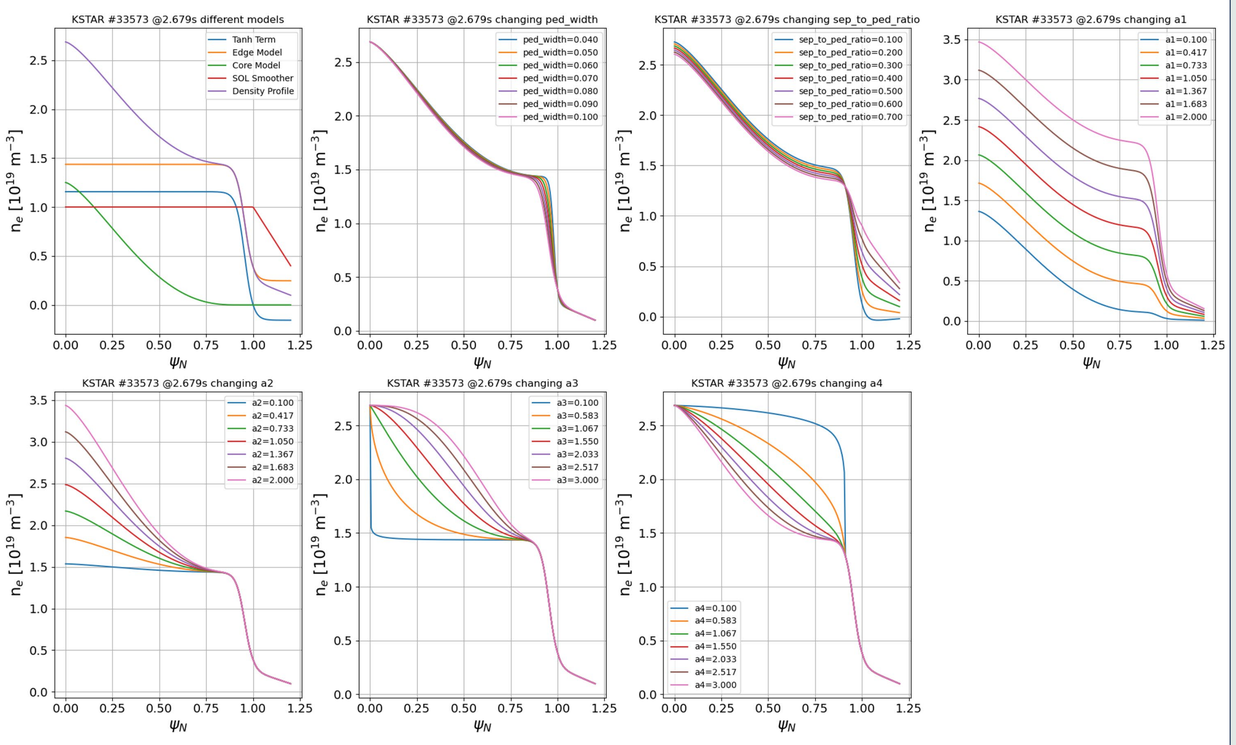
(c) Scrape off layer multiplier: $4-3\psi$

$$s(\psi)=\begin{cases}1 & (1\geq\psi\geq 0)\\ 4-3\psi & (\psi>1)\end{cases}$$

(d)
$$n_{e0}(\psi)=\begin{cases}\text{Edge model} & (\psi\geq\psi_t)\\ \text{Edge model + Core model} & (\psi<\psi_t)\end{cases}$$

$$n_e(\psi)=n_{e0}\times s$$

< Fig.1. Descriptions of the fitting model >



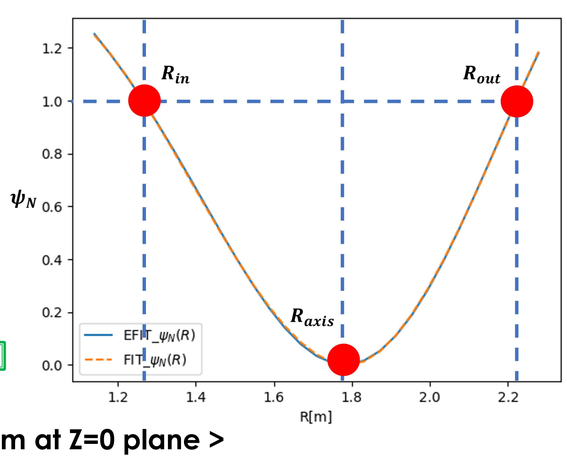
< Fig.2. Sensitivity check of the model >

2. Parametrize flux mapping to real-space

R : spatial domain from 1.1 to 2.4 (33 points)

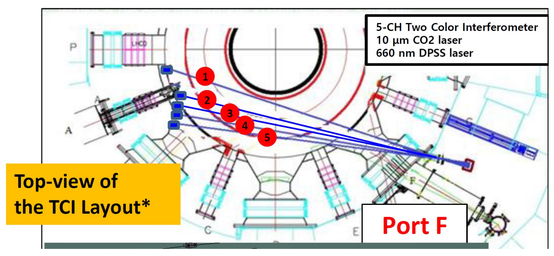
$R < R_{axis}$: $R2=\frac{(R-R_{axis})}{(R_{axis}-R_{in})}$, $y=b_1\times R2^2+(b_1-1)\times R2^3$

$R \geq R_{axis}$: $R2=\frac{(R-R_{axis})}{(R_{out}-R_{axis})}$, $y=b_2\times R2^2+(1-b_2)\times R2^3$

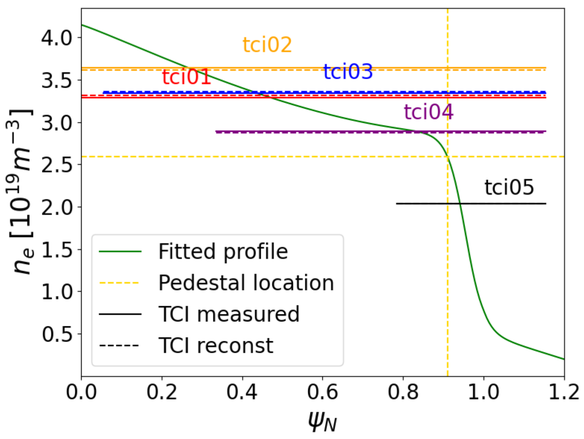


< Fig.3. Equilibrium at Z=0 plane >

3. Fitting the model with TCI



< Fig.4. Top view of TCI at KSTAR >



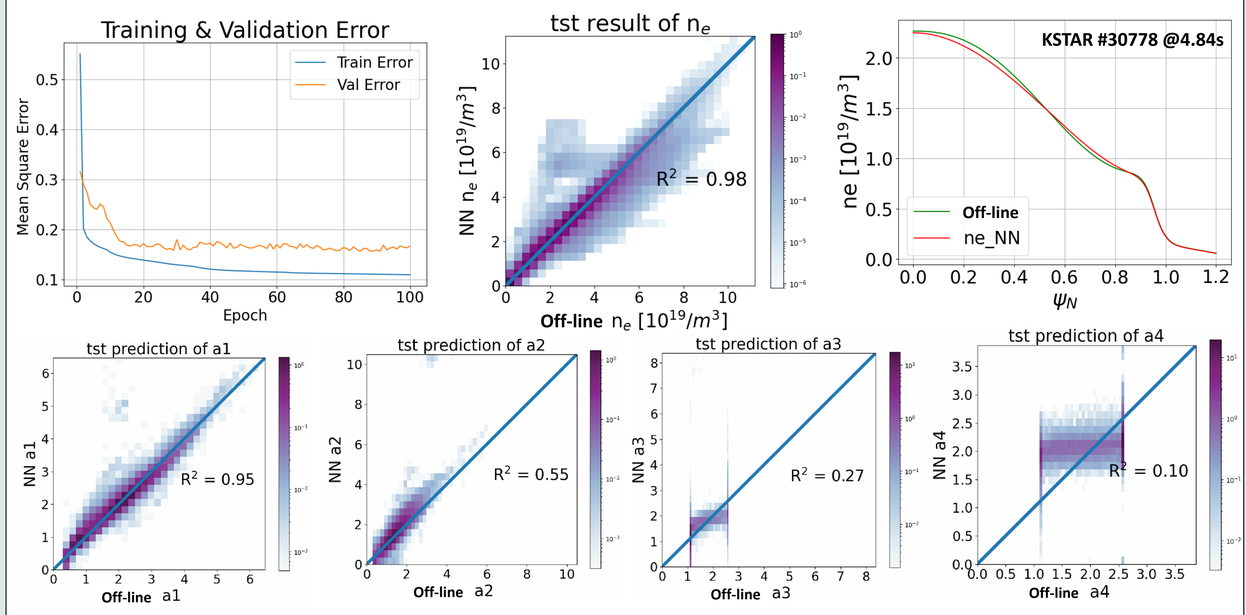
< Fig.5. Reconstructed ne profiles >

4. Neural network with 2022 KSTAR experimental data

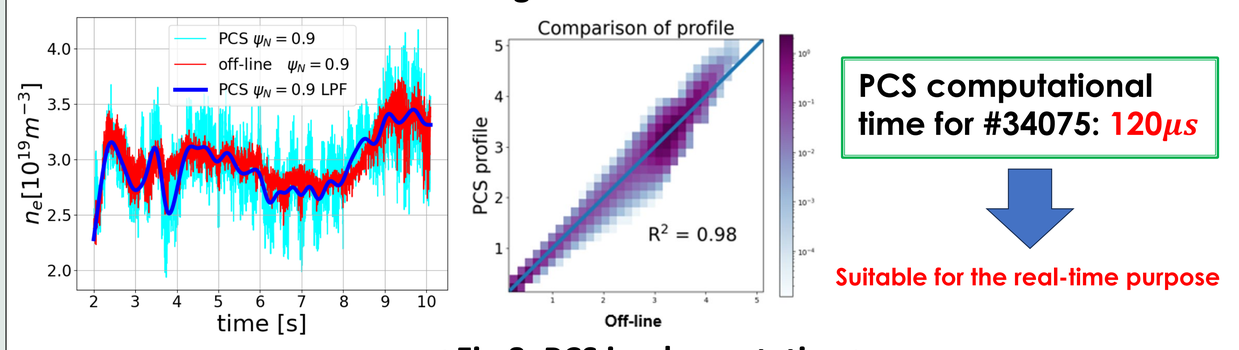
```
Activation functions are Relu with biases.
Model: "sequential"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 dense (Dense)               (None, 20)                220

 dense_1 (Dense)             (None, 30)                630

 dense_2 (Dense)             (None, 10)                310

 dense_3 (Dense)             (None, 4)                 44

=================================================================
Total params: 1,204
Trainable params: 1,204
Non-trainable params: 0
_________________________________________________________________
```

< Fig.6. Model description >

1. Training dataset [237,718,208 ($\sim 10^8$)]
2. Validation dataset [46,906 ($\sim 10^4$)]
3. Test dataset [46,907 ($\sim 10^4$)]



< Fig.7. NN test results >



PCS computational time for #34075: 120μs

Suitable for the real-time purpose

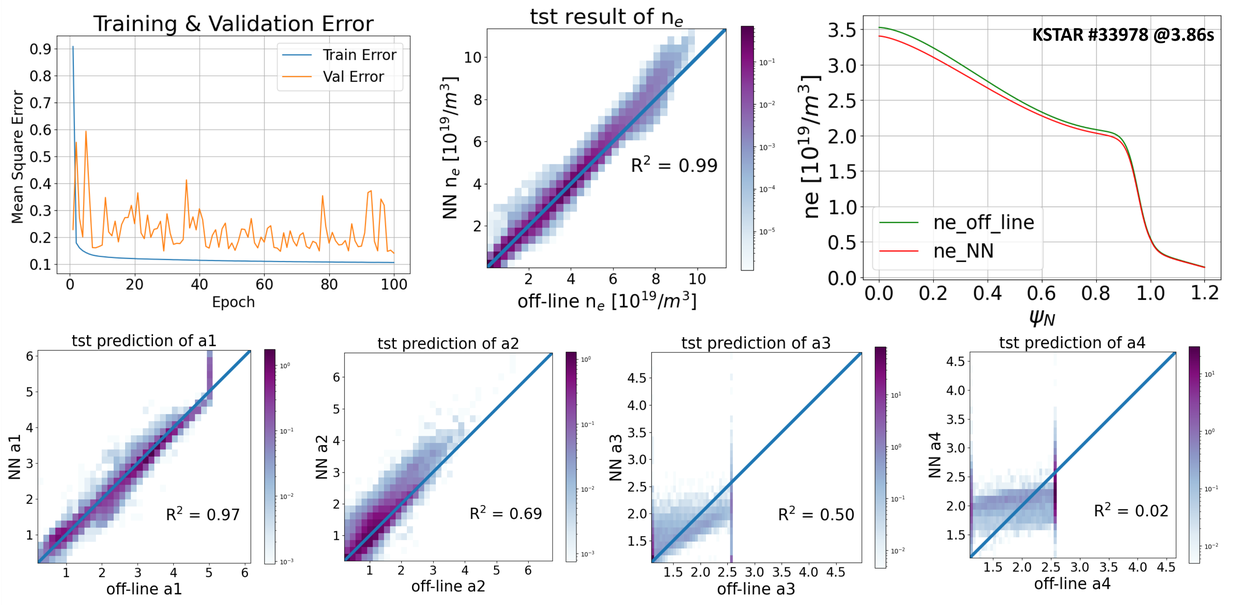
< Fig.8. PCS implementation >

5. Neural network with 2023 KSTAR experimental data

```
Layer (type)                 Output Shape              Param #
=================================================================
dense (Dense)                (None, 20)                220

batch_normalization_0        (None, 20)                80

activation (tanh)            (None, 20)                0

dense_1 (Dense)              (None, 10)                210

batch_normalization_1        (None, 10)                40

activation_1 (tanh)          (None, 10)                0

dense_2 (Dense)              (None, 4)                 44

activation_2 (relu)          (None, 4)                 0

=================================================================
Total params: 594
Trainable params: 534
Non-trainable params: 60
_________________________________________________________________
```

< Fig.9. Model description >

1. Training dataset [237,718,208 ($\sim 10^8$)]
2. Validation dataset [33,591 ($\sim 10^4$)]
3. Test dataset [33,592 ($\sim 10^4$)]



< Fig.10. NN test results >

6. Conclusion & Future works

1. Real-time electron density profile reconstruction algorithm has been implemented at the KSTAR PCS.
2. The density at ψ_N=0.2 and 0.9 will be our control target with the actuators of gas puff, pellet, SMBI, and RMP for the experiment on January 3rd. (Tentative)
3. The controller can be used to help achieve high-beta and hybrid scenarios.

Acknowledgement

1. Lee, S. G., et al. "Overview and recent progress of KSTAR diagnostics." *Journal of Instrumentation* 17.01 (2022): C01065.
2. Snyder, P. B., et al. "ELMs and constraints on the H-mode pedestal: peeling–ballooning stability calculation and comparison with experiment." *Nuclear fusion* 44.2 (2004): 320.

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