



SMART SOLAR POWER

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project owner

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The Problem

■ Time Series Forecast

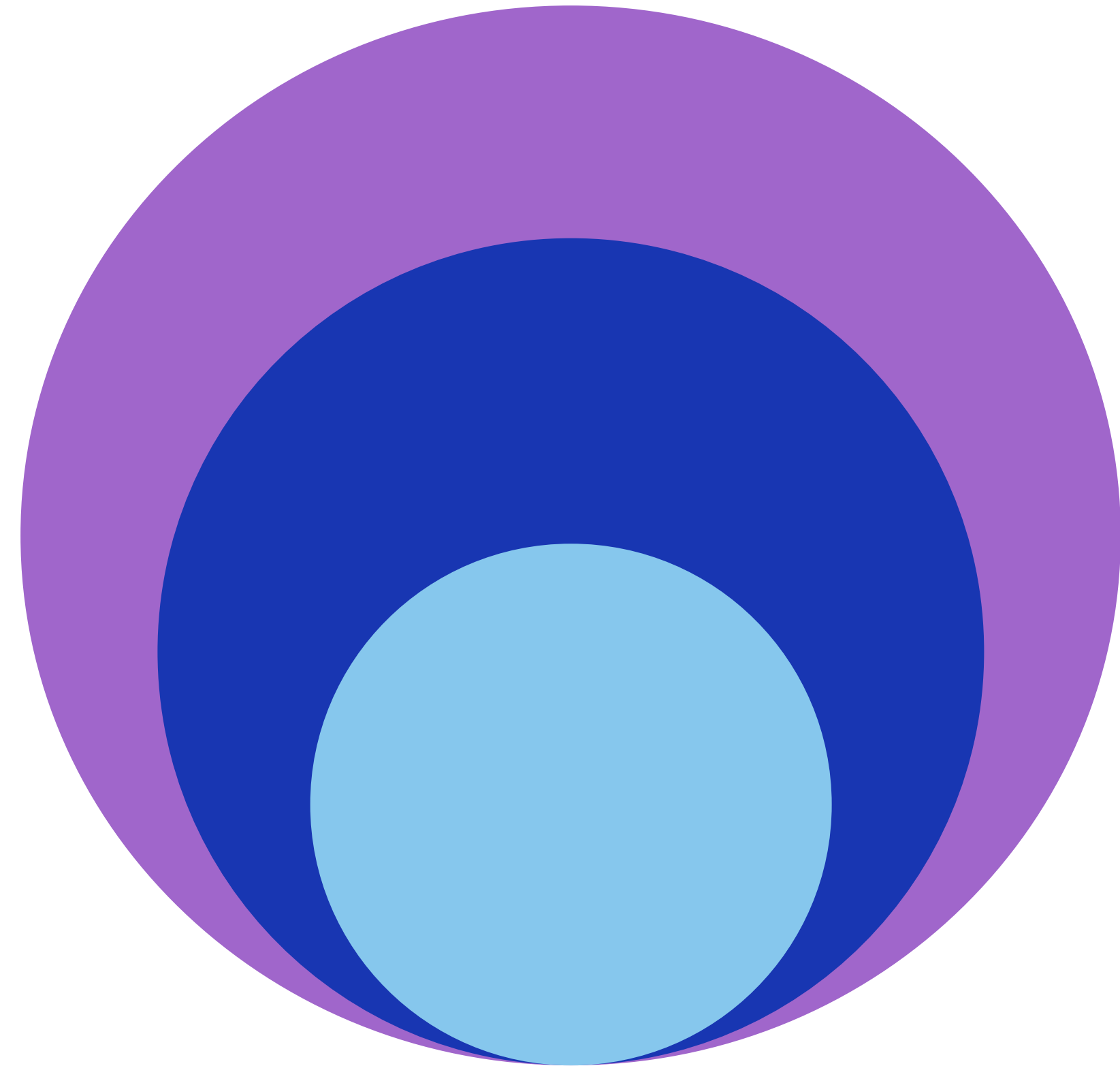
- Tartu

■ Interval Flux Rate on 5min

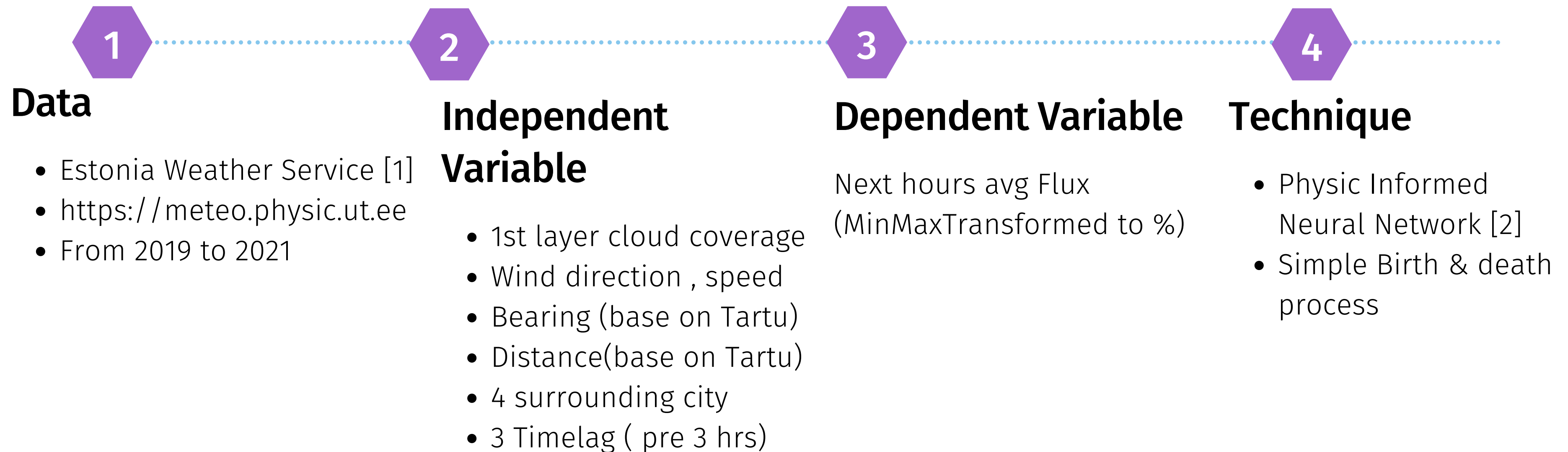
- Model Train on 1 hrs avg
- Inference on 5mins interval

(Base on the propriety of continuous time modelling of birth and death process)

■ Washing Machine Scheduling



Our Approach



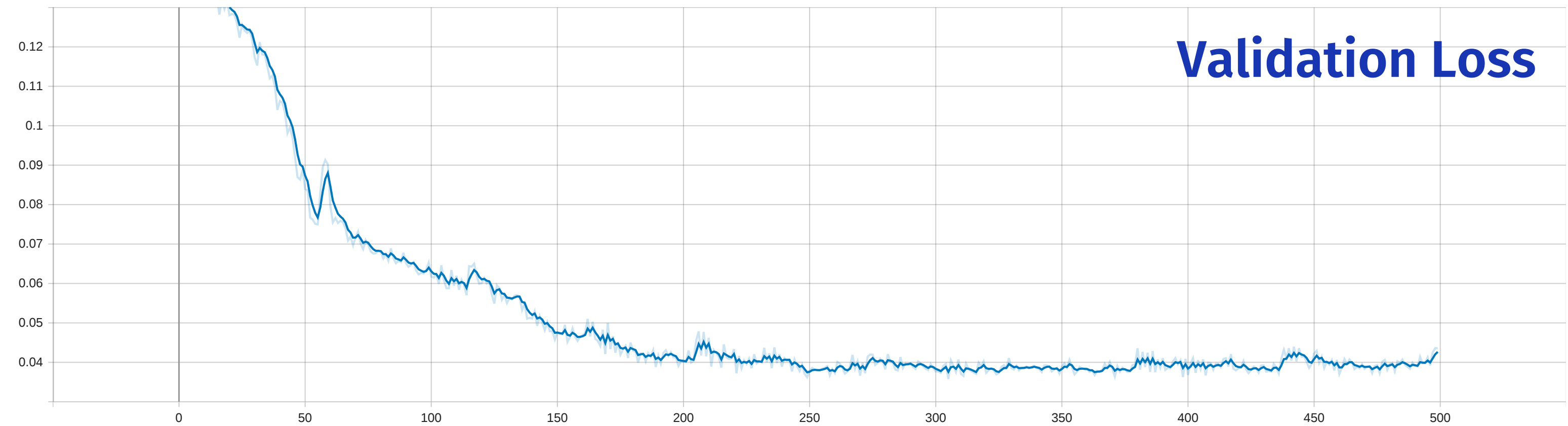
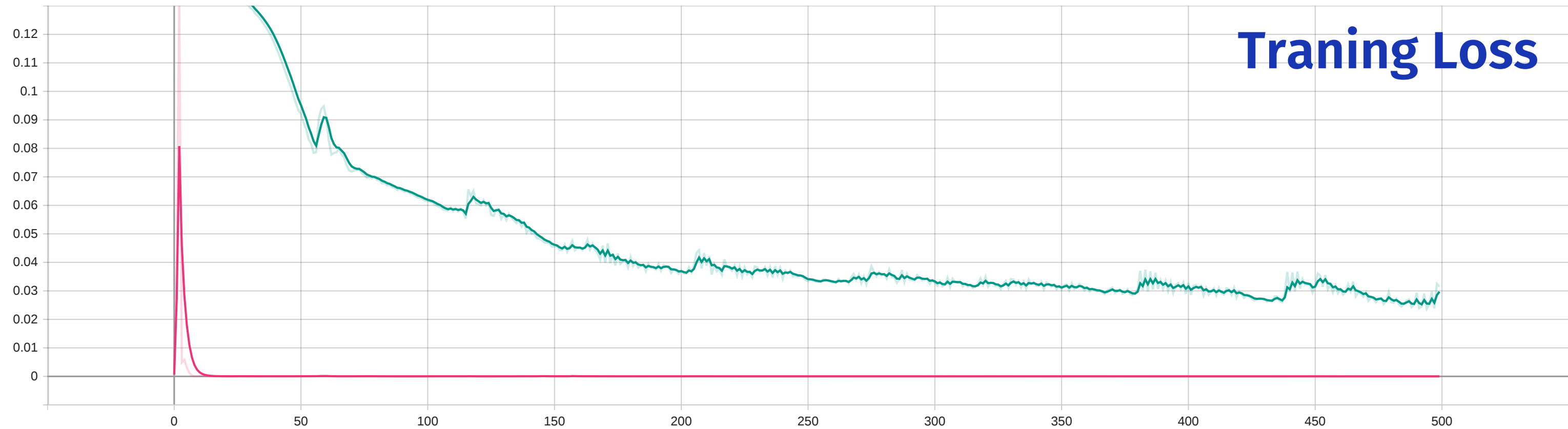
Training/Validation Results (hour avg)

Epocs
500 epochs - L1loss
converage - 300 epochs
avg validation loss (0.04) ~ 4% in average (max flux 1132)

Data	
Training	2019
Validation	2020
Testing	2021 until Nov



CPINN Loss Plot

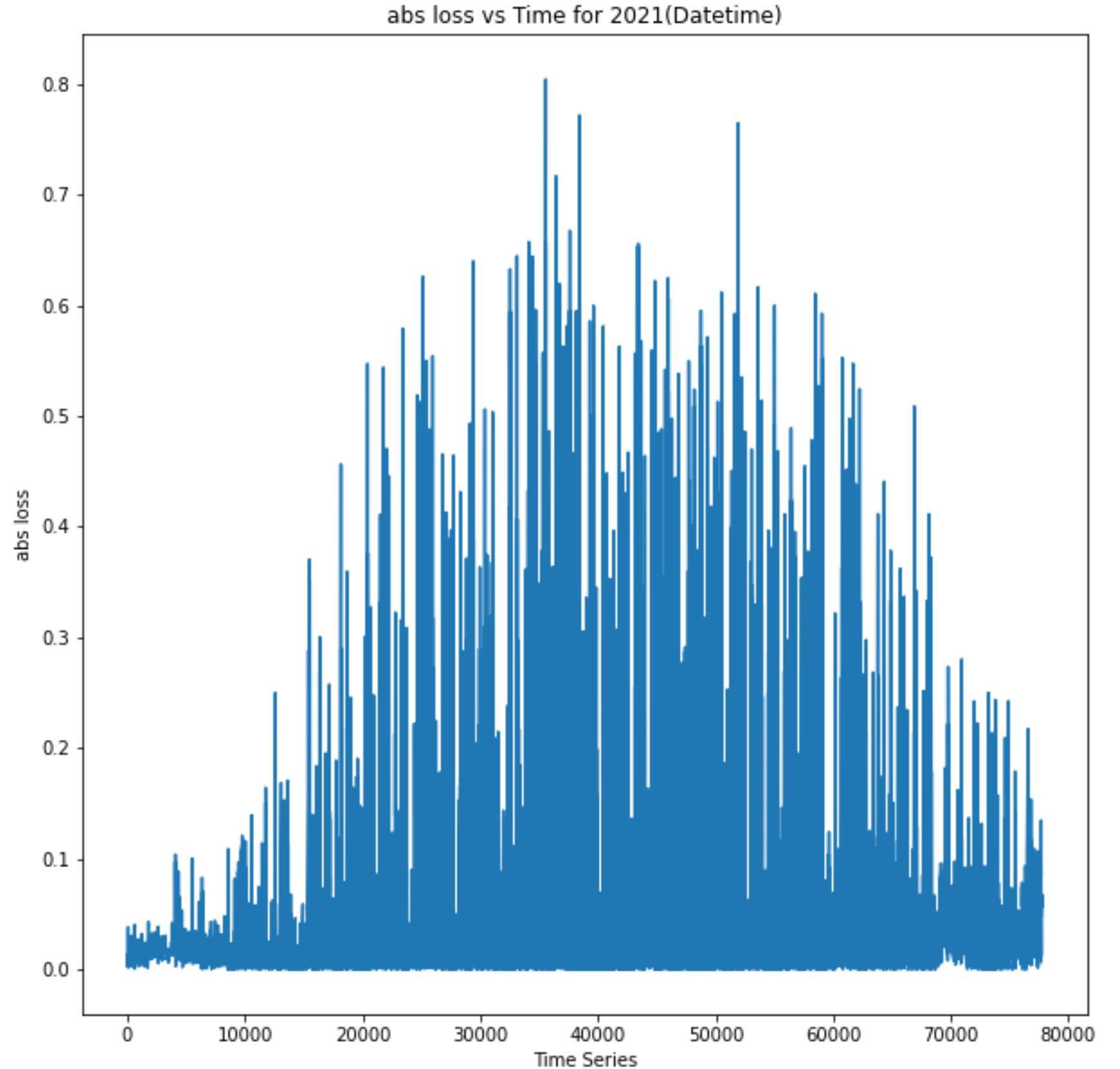
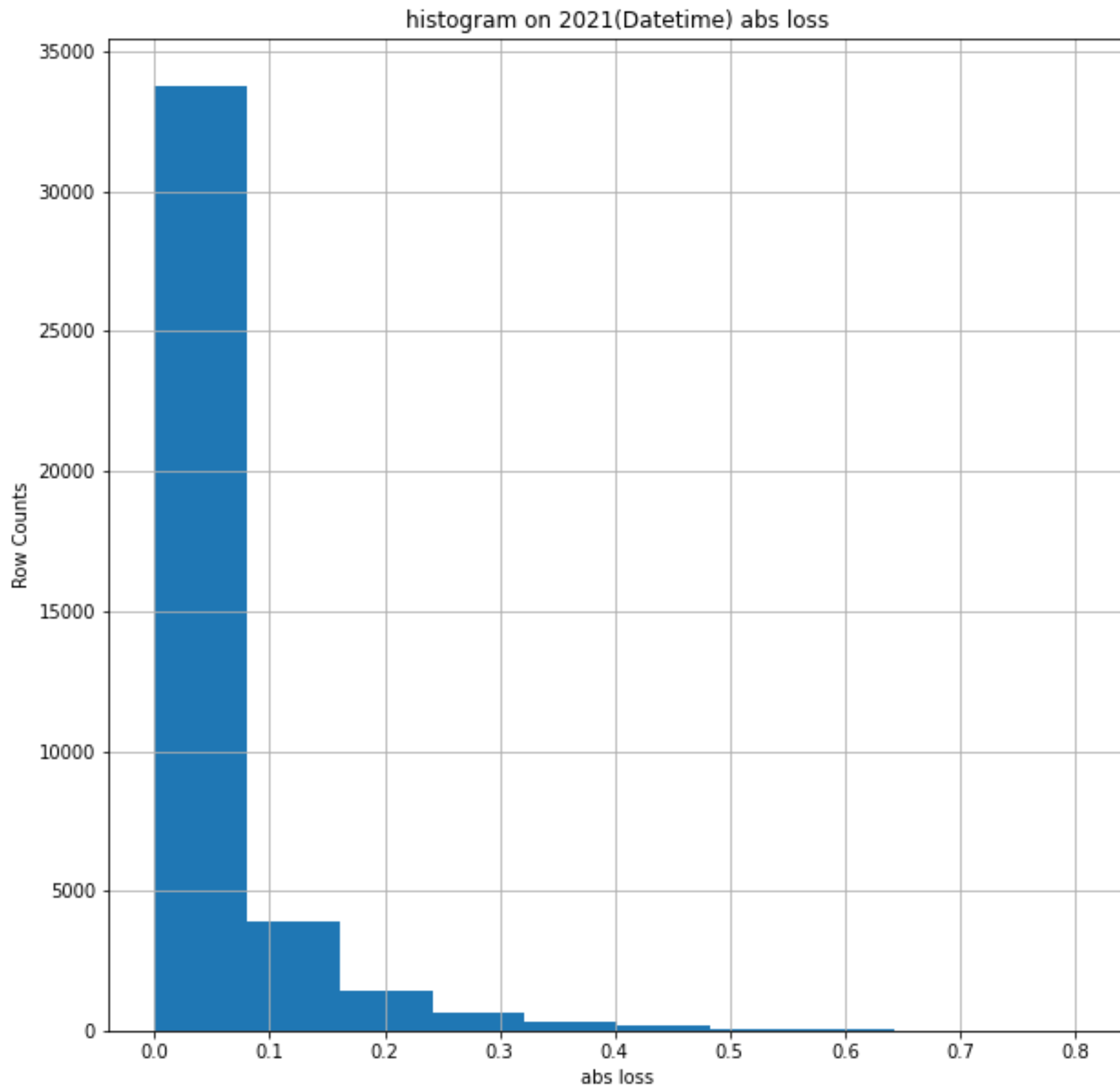


Testing Results on loss (5min Interval -max flux 1132)

All hours(Day+Night)	2019 (77828 rows)	2020 (97837 rows)	2021 (84839)
avg loss	0.024 (2.4%)	0.025 (2.5%)	0.028 (2.8%)
std. deviation	0.05 (5%)	0.05 (5%)	0.057 (5.7%)
median	0.0039 (0.4%)	0.0037 (0.37%)	0.006 (0.6%)
75% quantile	0.028 (2.8%)	0.027 (2.7%)	0.032 (3.2%)
Max	0.735 (73%)	0.8 (80%)	0.8 (80%)

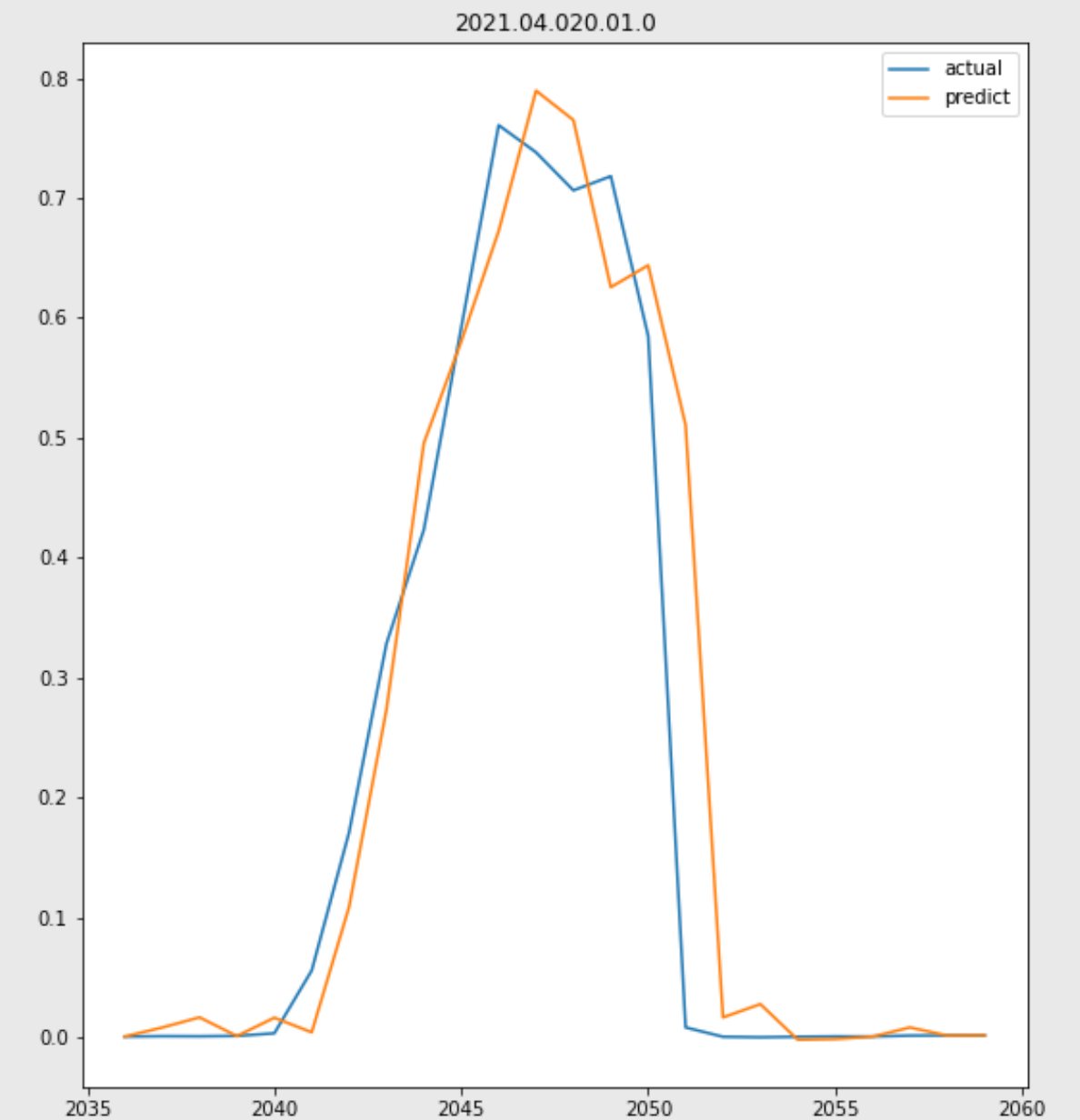
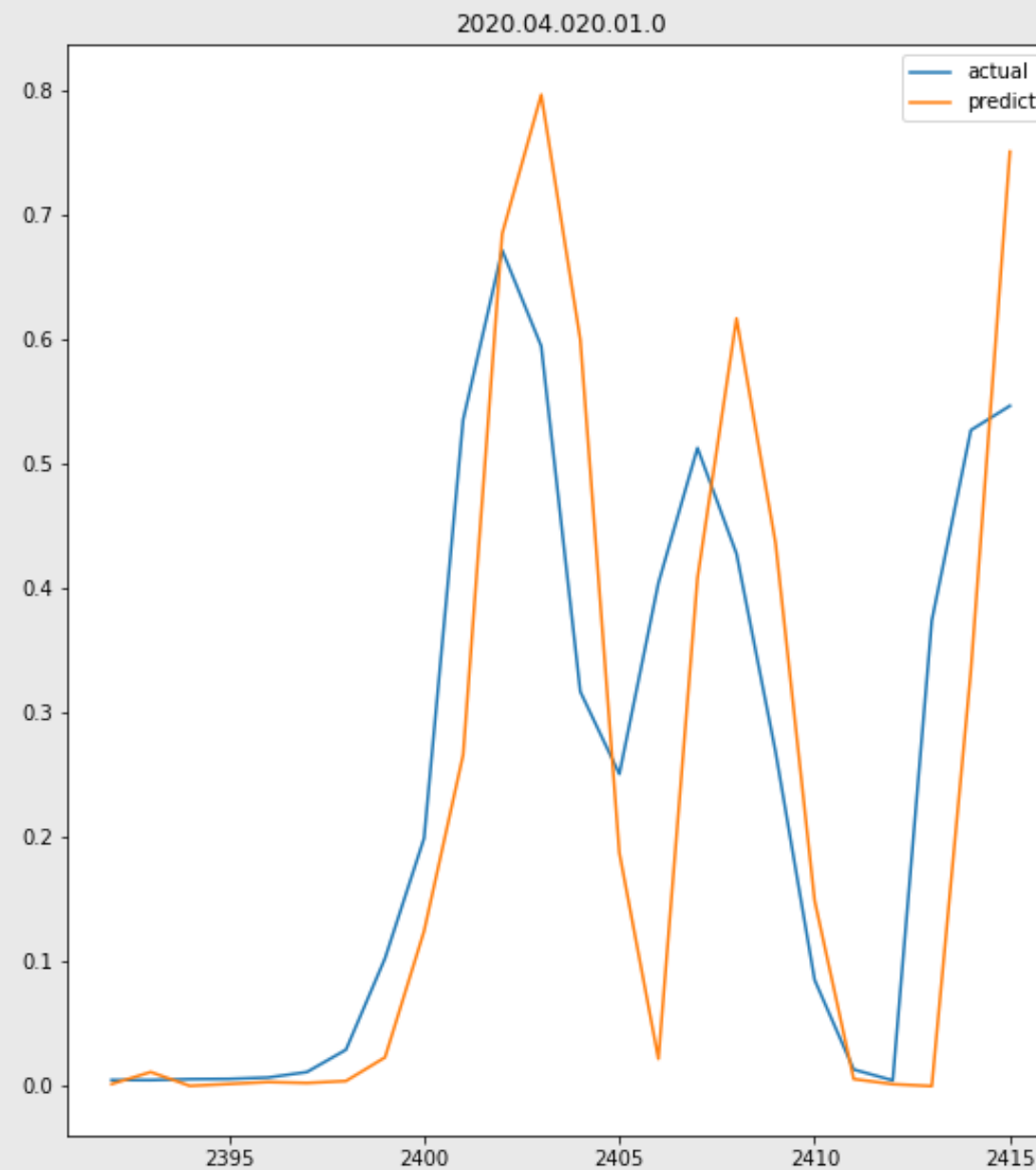
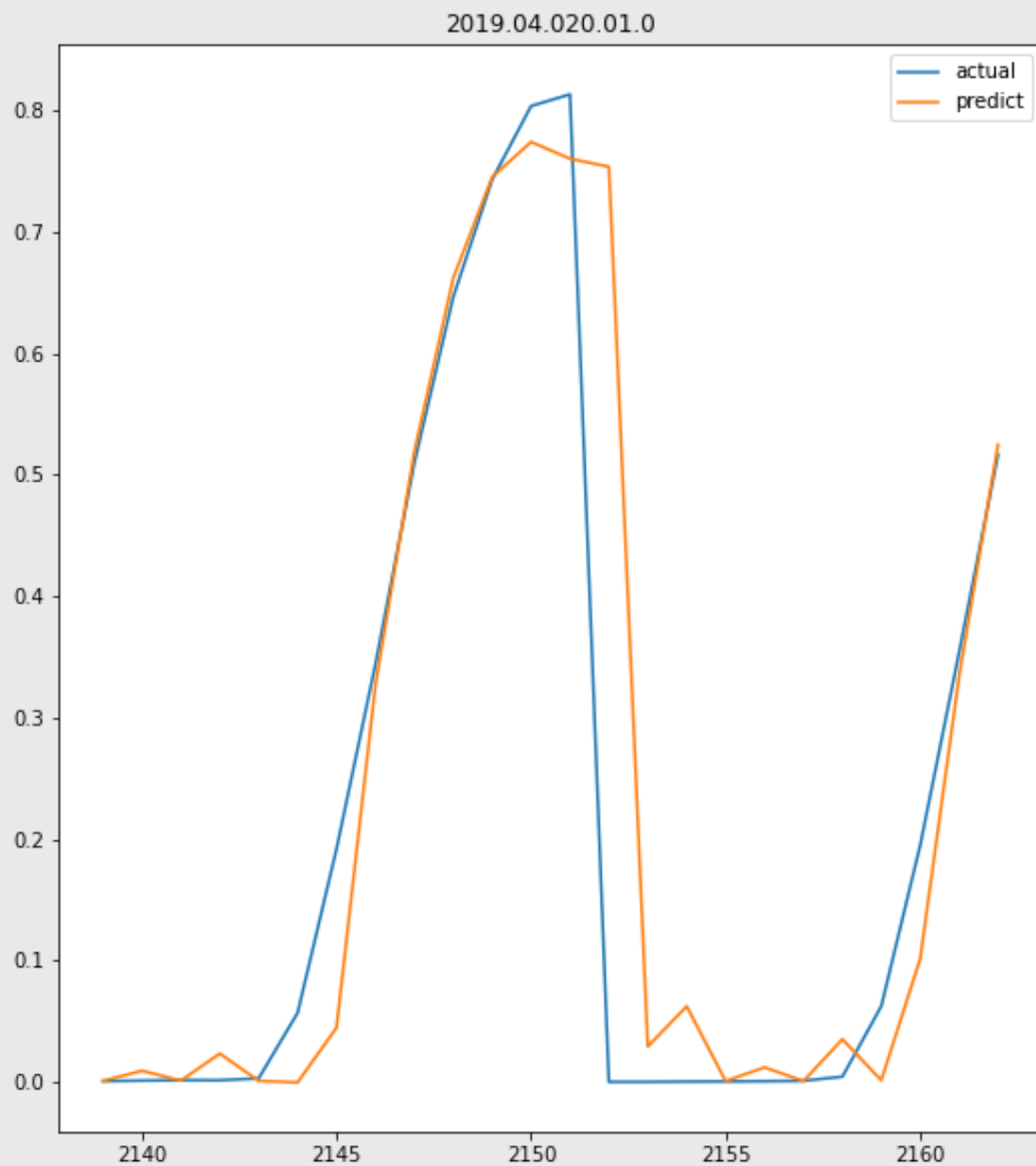
Only Date time	2019	2020	2021
avg loss	0.047 (4.7%)	0.05 (5%)	0.052 (5.2%)
std. deviation	0.0615 (6.15%)	0.069 (6.9%)	0.071 (7.1%)
median	0.029 (3%)	0.029 (3%)	0.030 (3%)
75% quantile	0.056 (5.6%)	0.059 (5.9%)	0.059 (5.9%)
Max	0.735 (73%)	0.8 (80%)	0.8 (80%)

Testing Results on loss (5min Interval -max flux 1132)



Expectations vs Results (Hours avg)

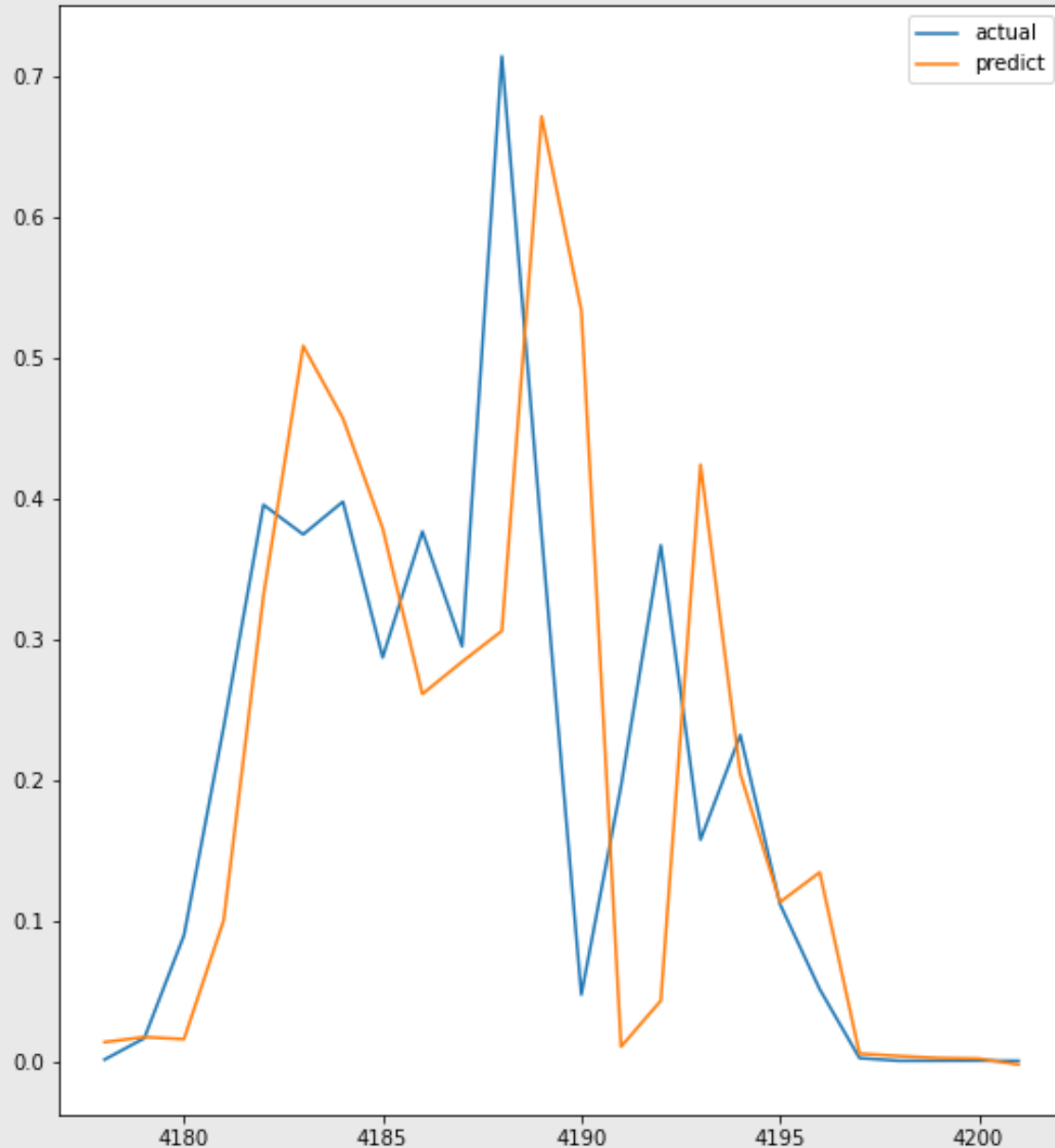
- random selected date
- 24 hours intervals



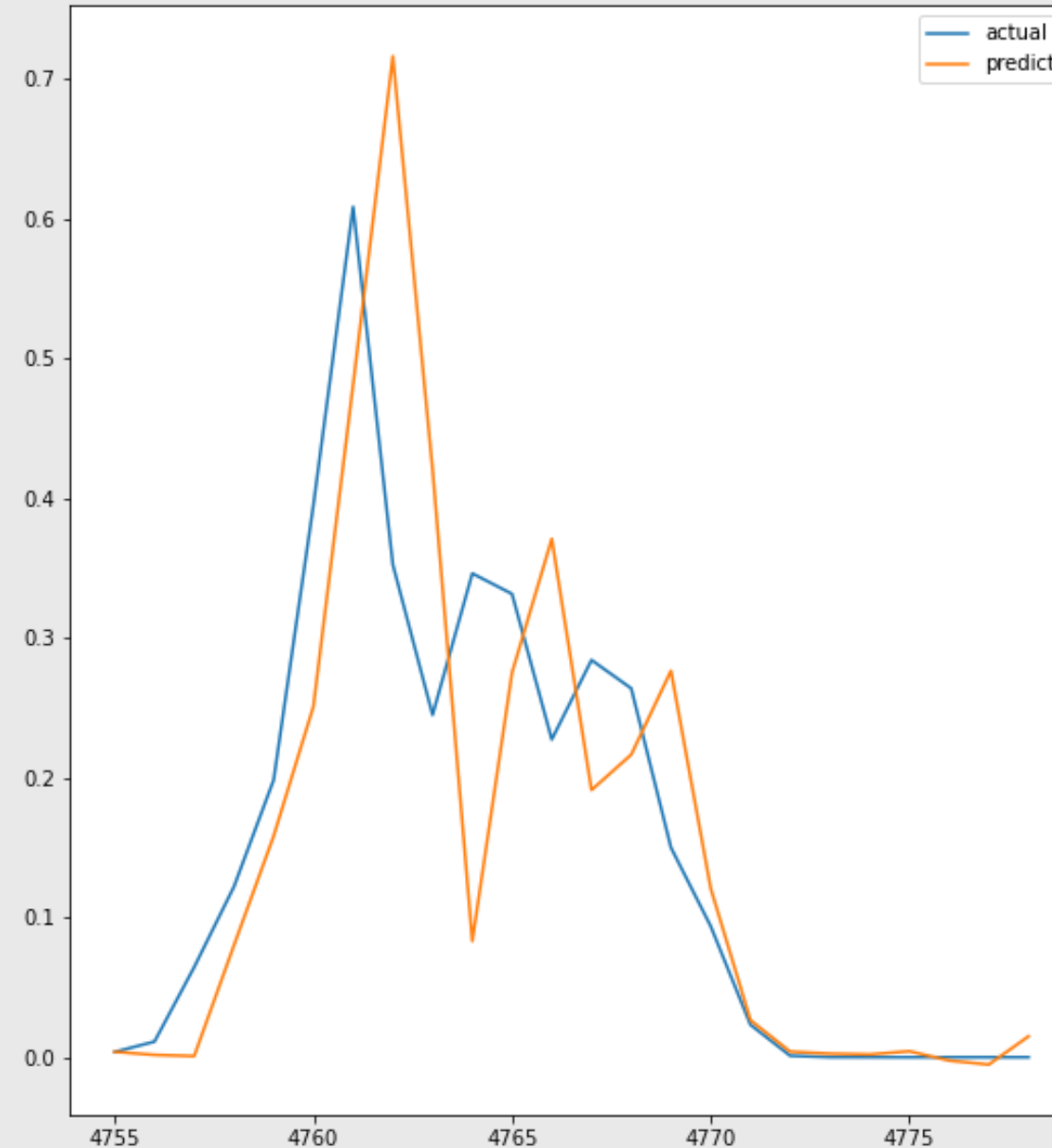
Expectations vs Results (Hours avg)

- random selected Month,date,hour
- 24 hours intervals

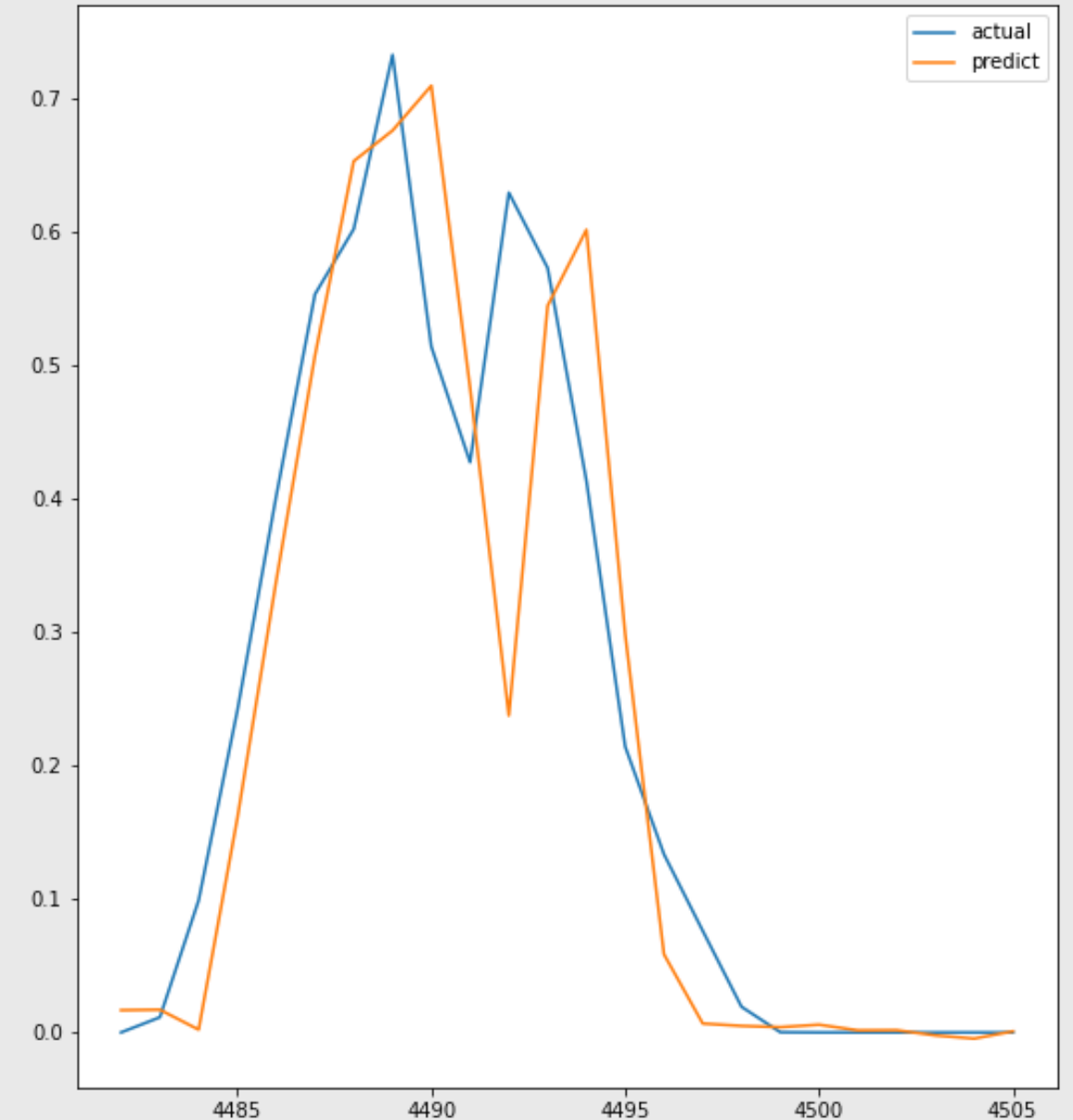
2019.08.06.04.0



2020.08.06.04.0

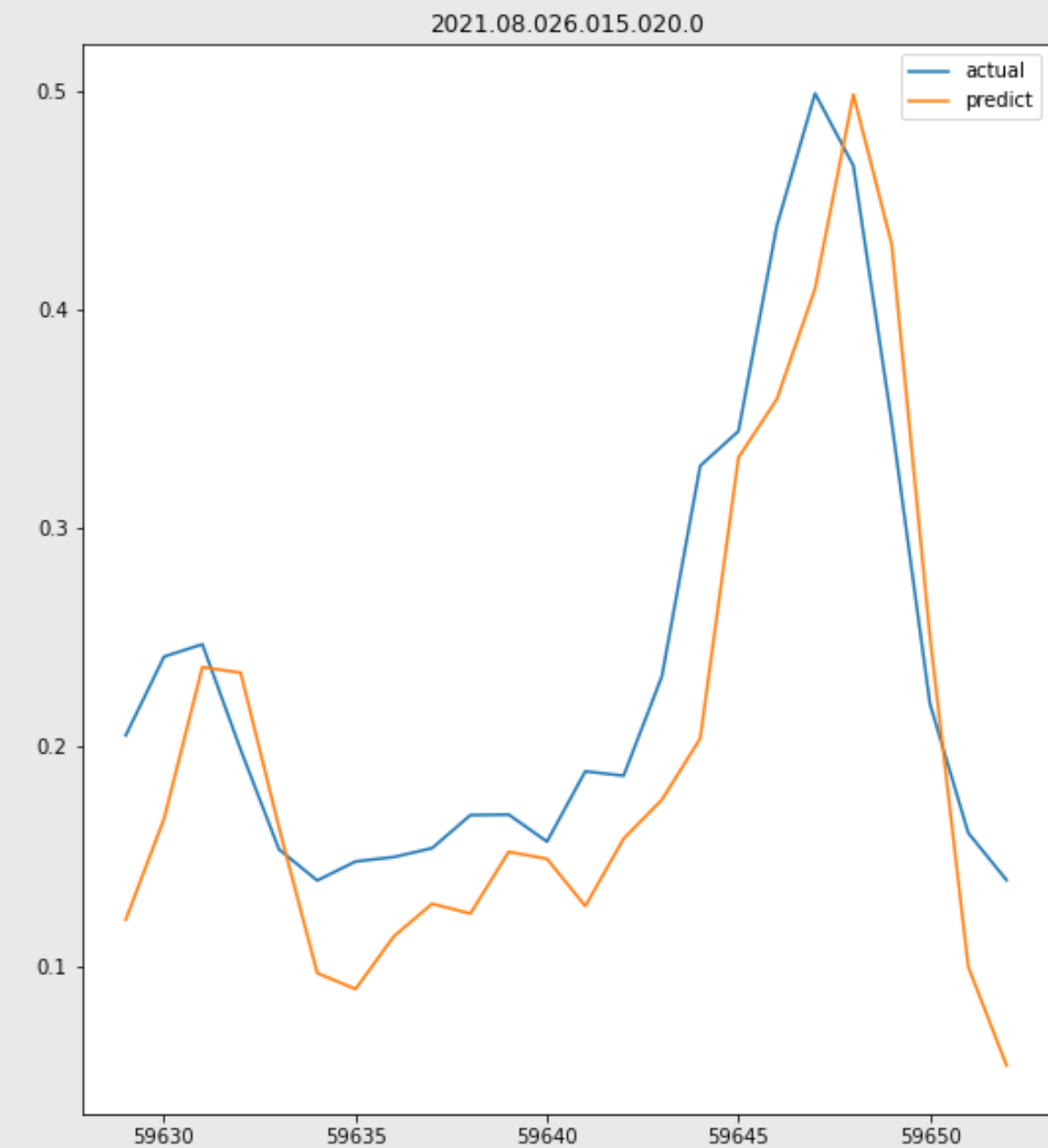
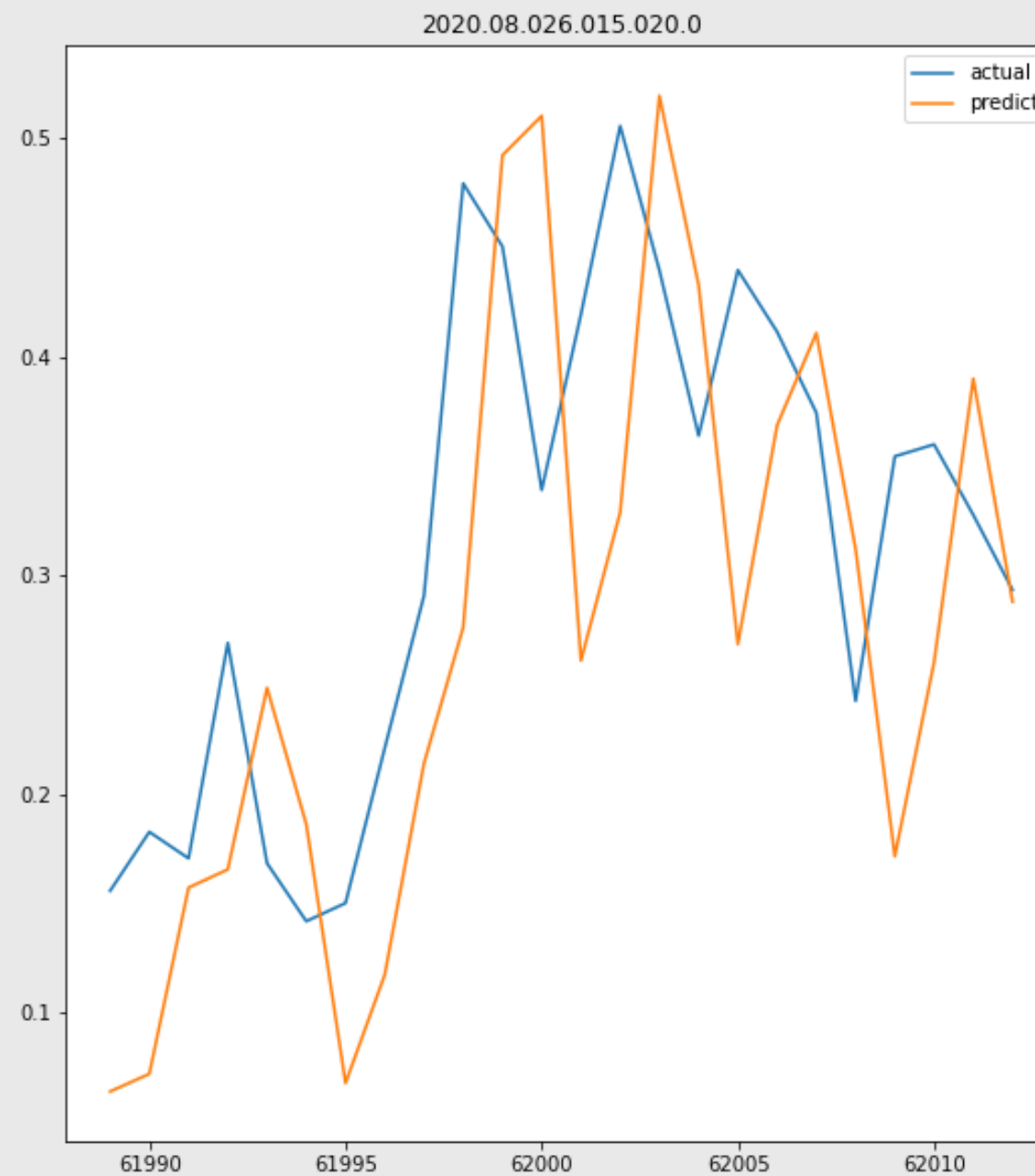
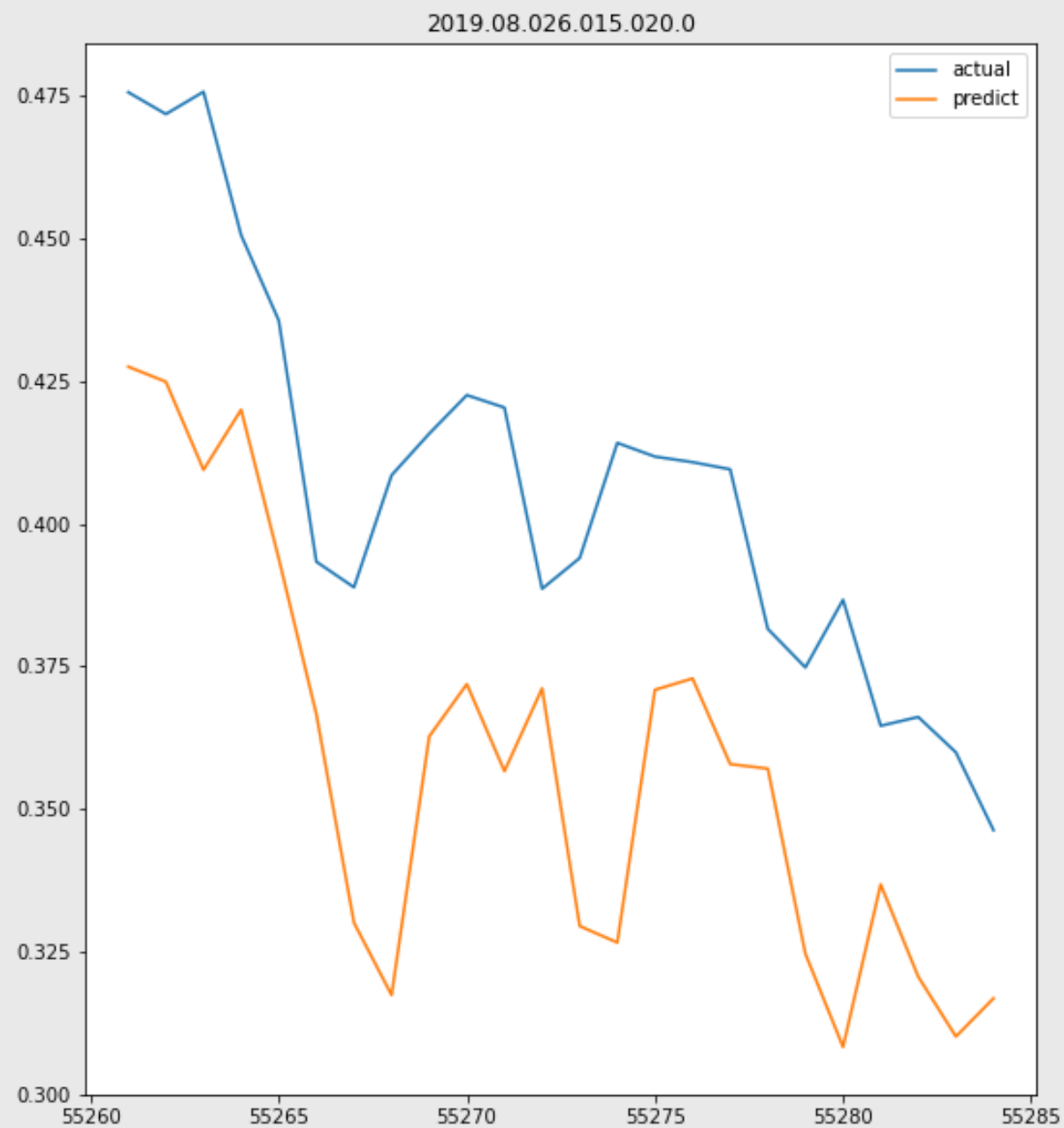


2021.08.06.04.0



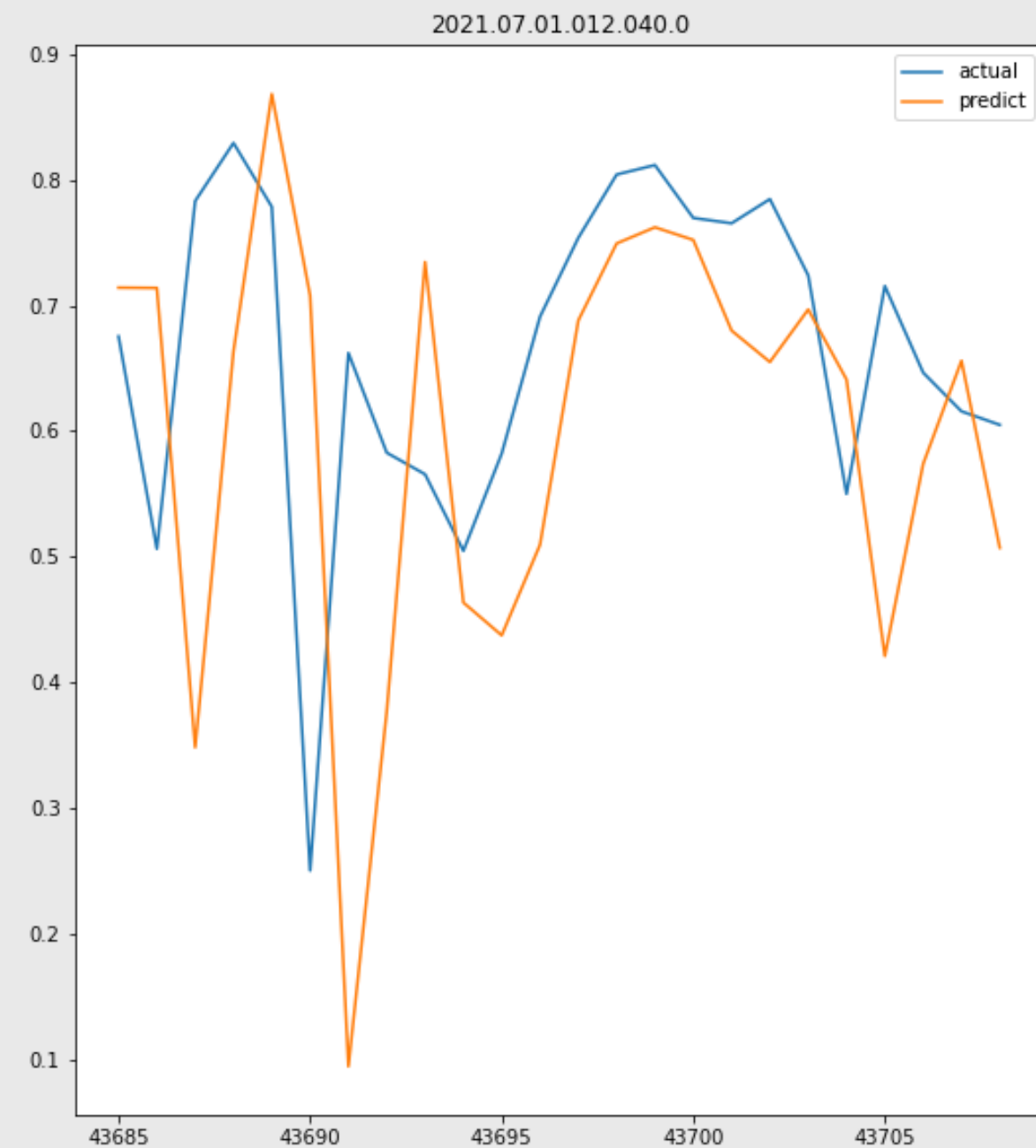
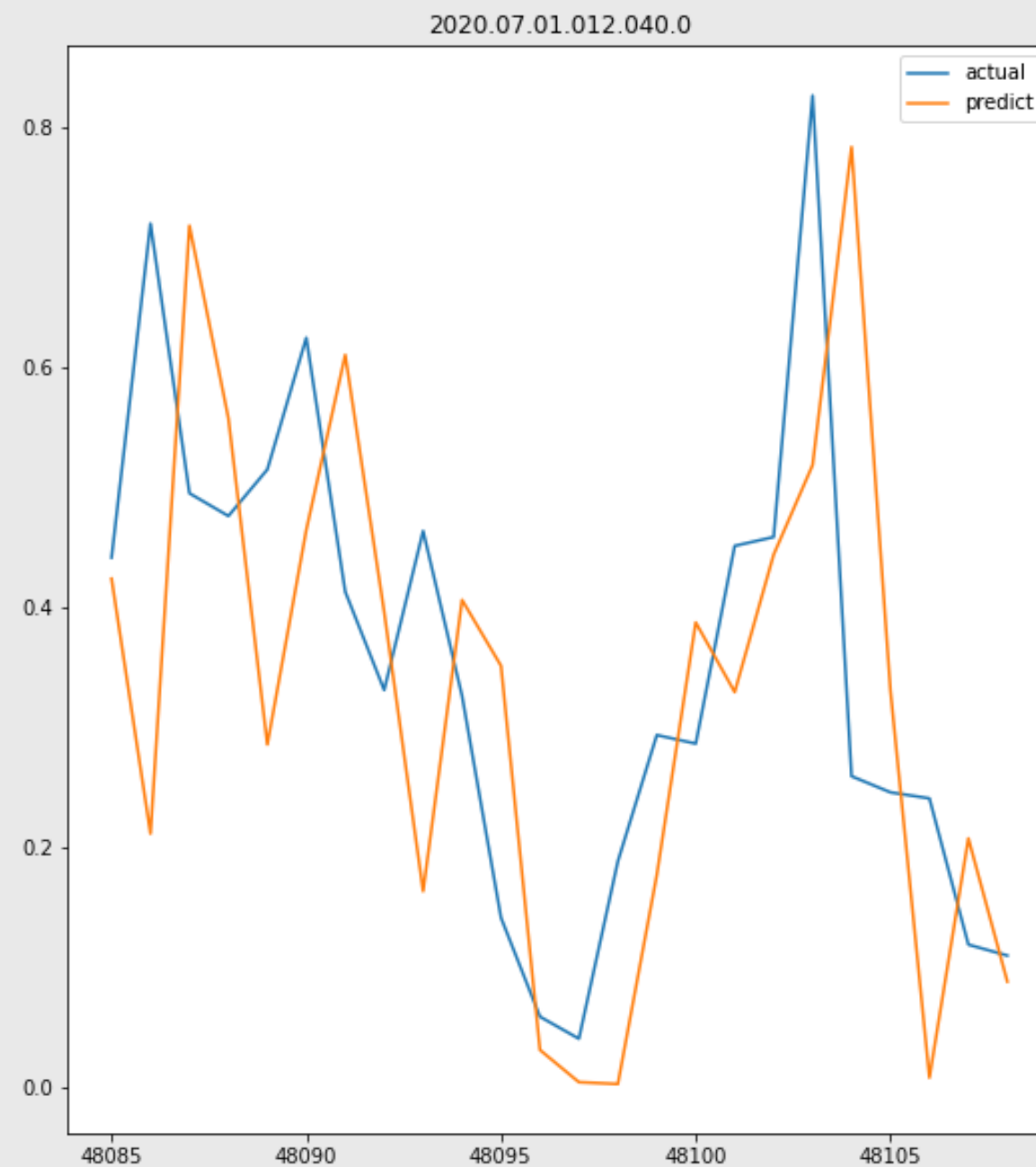
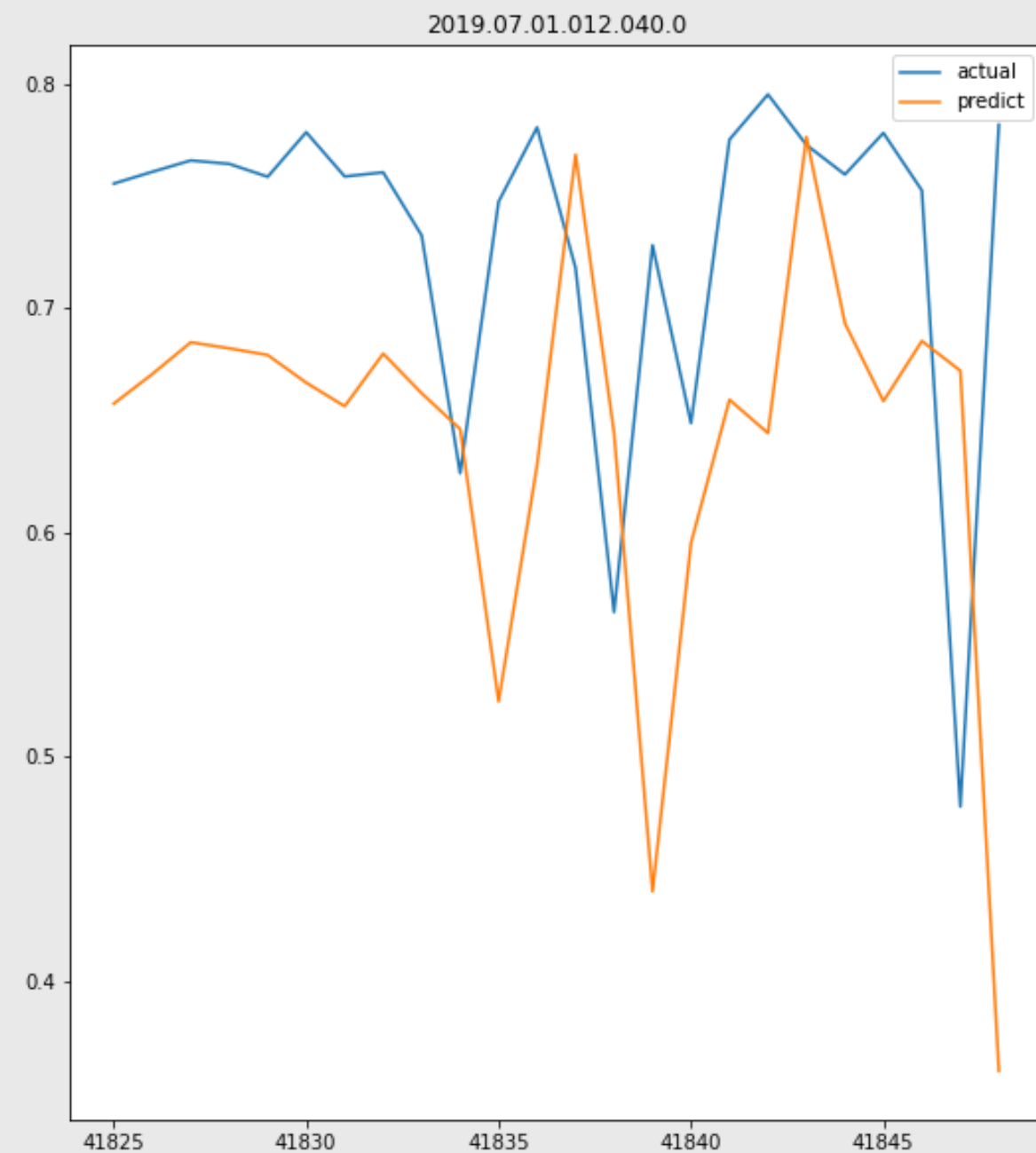
Expectations vs Results (5mins)

- random selected Month,date,hours,mins
- 2 hours intervals

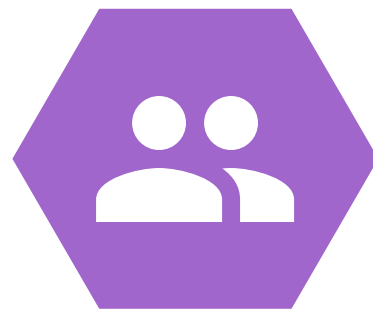


Expectations vs Results (5mins)

- random selected Month,date,hours,mins
- 2 hours intervals

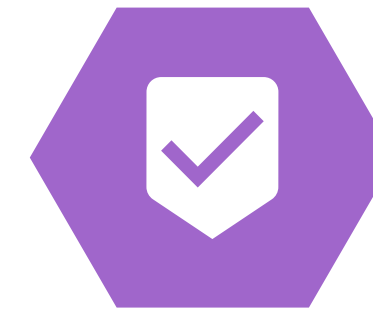


We've learned



Soft Skills

- Out of box thinking
- Make a compromise from different opinions
- How to interact with people from different cultures



Technical Skills

- Pytorch
- Data Mining
- Basic Idea on Time Series Forecast
- Physic Informed Neural Network [2]
- Data Exploration and Transformation (pandas)

References

[1] Estonia Weather Service

<https://www.ilmateenistus.ee/?lang=en>

<https://meteo.physic.ut.ee/>

[2] Physic Informed Neural Network

<https://benmoseley.blog/my-research/so-what-is-a-physics-informed-neural-network/>

[https://github.com/jayroxis/PINNs/blob/master/Burgers%20Equation/Burgers%20Inference%20\(PyTorch\).ipynb](https://github.com/jayroxis/PINNs/blob/master/Burgers%20Equation/Burgers%20Inference%20(PyTorch).ipynb)

<https://maziarraissi.github.io/PINNs/>

Physics Informed Deep Learning (Part I): Data-driven Solutions of Nonlinear Partial Differential Equations

Physics Informed Deep Learning (Part II) Data-driven Discovery of Nonlinear Partial Differential Equations

[3] Smart Solar Power Project Source Code

https://github.com/tik65536/2021UTML_Solar

Reference2

hourly flux std. deviation
(base on 5mins data) 2019

```
1 stat[('Irradiation flux', 'std')].describe()
```

```
count      8453.000000
mean        23.878684
std         42.418104
min          0.000000
25%          0.270648
50%          3.291532
75%         31.456848
max         347.276330
Name: (Irradiation flux, std), dtype: float64
```

Correlation of cloud coverage and flux

```
1 pd.DataFrame(np.vstack((resultI1,resultA2)).T).corr() #Monthly Correlation (avg 2019)
```

```
0      1
0  1.000 -0.889
1 -0.889  1.000
```

```
1 pd.DataFrame(np.vstack((resultI2,resultA1)).T).corr() #Daily Correlation (avg 2019)
```

```
0      1
0  1.000000 -0.456883
1 -0.456883  1.000000
```

```
1 pd.DataFrame(np.vstack((resultI3,resultA3)).T).corr() # Yearly Correlation (avg 2019)
```

```
0      1
0  1.000000 -0.895039
1 -0.895039  1.000000
```

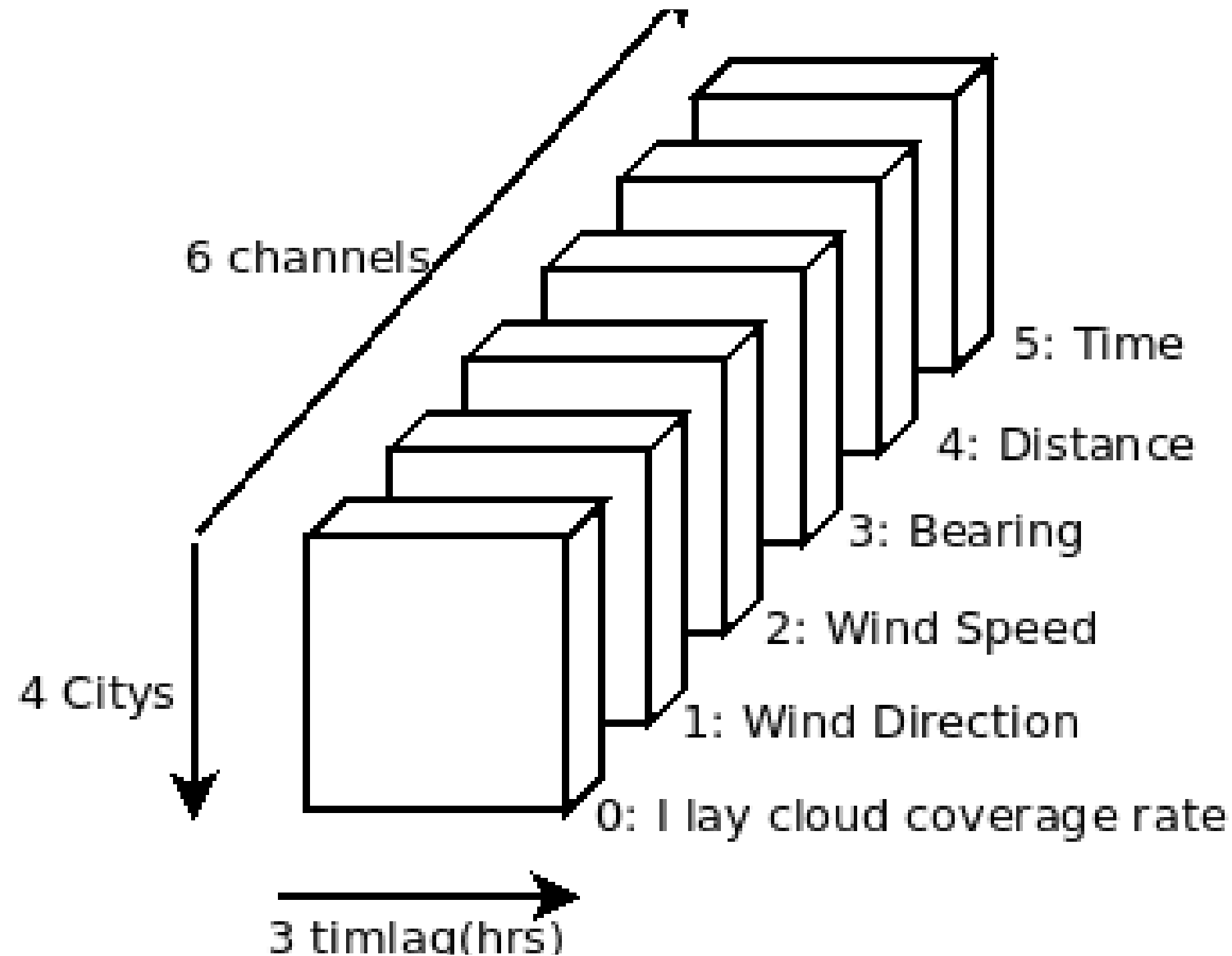
Reference3

Correlation of cloud coverage between Tartu,
Turi,Voru,Vaike,Vilsandi

```
: 1 data2019[['I_layer_amount', 'I_layer_amount_Turi', 'I_layer_amount_Voru', 'I_layer_amount_Vaike', 'I_layer_amount_Vilsandi']].corr()
```

	I_layer_amount	I_layer_amount_Turi	I_layer_amount_Voru	I_layer_amount_Vaike	I_layer_amount_Vilsandi
I_layer_amount	1.000000	0.605705	0.659917	0.603170	0.538266
I_layer_amount_Turi	0.605705	1.000000	0.526393	0.660447	0.596965
I_layer_amount_Voru	0.659917	0.526393	1.000000	0.528558	0.486318
I_layer_amount_Vaike	0.603170	0.660447	0.528558	1.000000	0.541491
I_layer_amount_Vilsandi	0.538266	0.596965	0.486318	0.541491	1.000000

CPINN model (Data Cube)

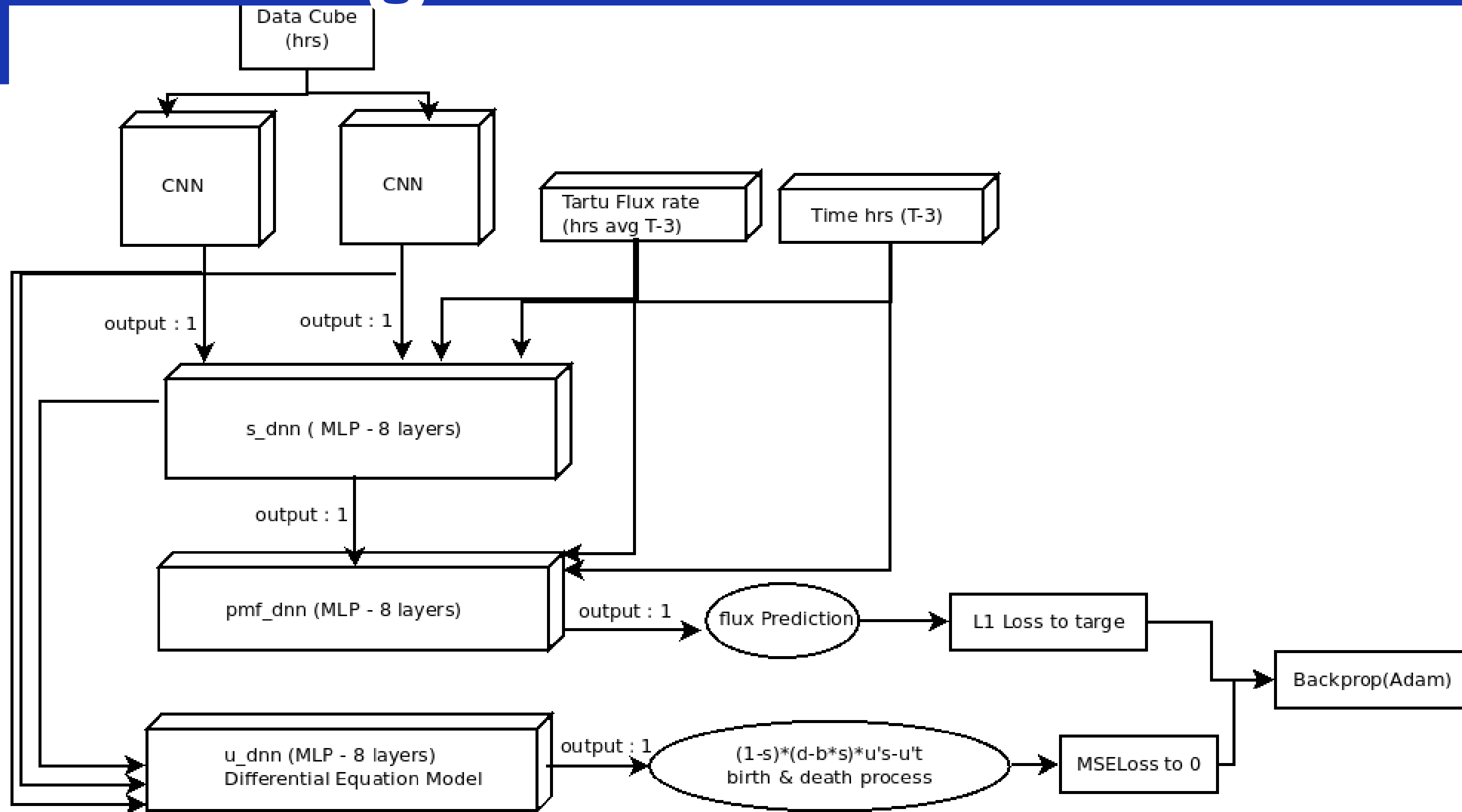


Time Encoding (Hrs):
 $\text{Time} = \text{Month}-1 + \text{hrs} * (1/23)$

Time Encoding (mins):
 $\text{Time} = \text{Month}-1 + \text{mins} * (1/23/60)$

CPINN model (Network Structure)

Training



CPINN model (Network Summary)

CNN Summary

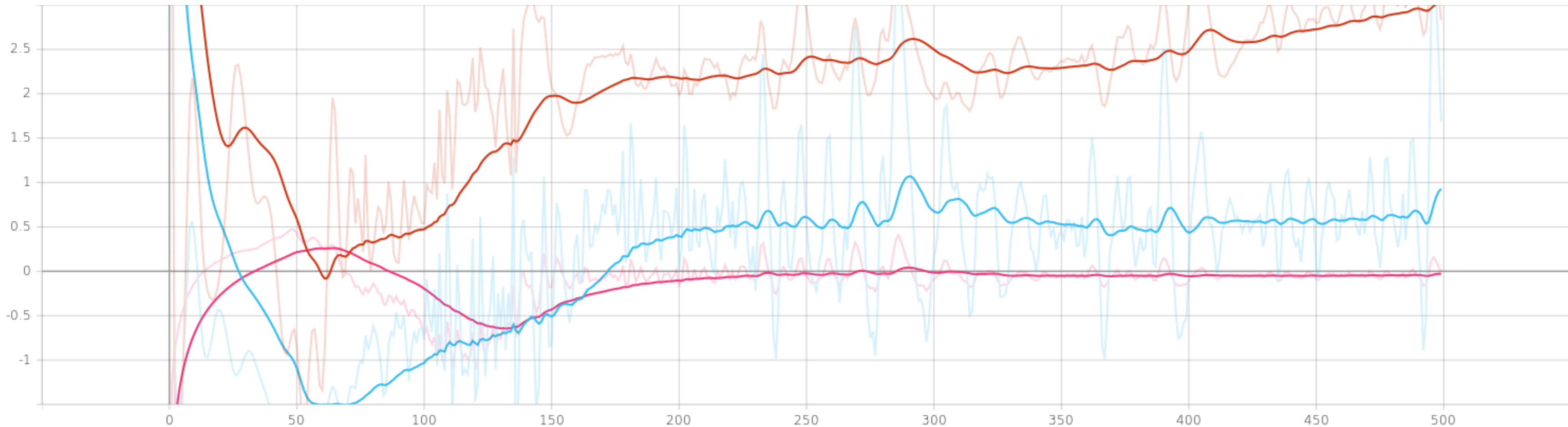
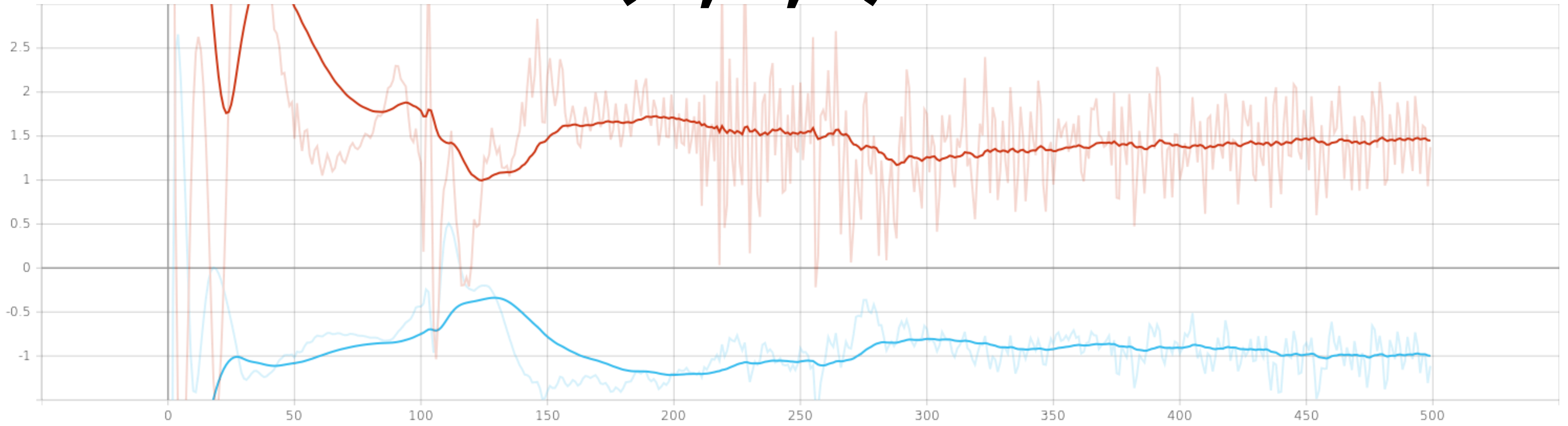
Training Set birth data len 7067
Validation Set birth data len 7885

```
CDNN(  
  (activation): ReLU()  
  (dnn1): Sequential(  
    (0): Conv2d(6, 64, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))  
    (1): ReLU()  
    (2): Conv2d(64, 128, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))  
    (3): ReLU()  
    (4): Conv2d(128, 128, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))  
    (5): ReLU()  
    (6): Flatten(start_dim=1, end_dim=-1)  
    (7): Linear(in_features=1536, out_features=1024, bias=True)  
    (8): ReLU()  
    (9): Linear(in_features=1024, out_features=256, bias=True)  
    (10): ReLU()  
    (11): Linear(in_features=256, out_features=1, bias=True)  
  )  
)
```

MLP Summary

Training Set birth data len 7067
Validation Set birth data len 7885
DNN(
 (layers): Sequential(
 (layer_0): Linear(in_features=17, out_features=40, bias=True)
 (activation_0): ReLU()
 (layer_1): Linear(in_features=40, out_features=40, bias=True)
 (activation_1): ReLU()
 (layer_2): Linear(in_features=40, out_features=40, bias=True)
 (activation_2): ReLU()
 (layer_3): Linear(in_features=40, out_features=40, bias=True)
 (activation_3): ReLU()
 (layer_4): Linear(in_features=40, out_features=40, bias=True)
 (activation_4): ReLU()
 (layer_5): Linear(in_features=40, out_features=40, bias=True)
 (activation_5): ReLU()
 (layer_6): Linear(in_features=40, out_features=40, bias=True)
 (activation_6): ReLU()
 (layer_7): Linear(in_features=40, out_features=40, bias=True)
 (activation_7): ReLU()
 (layer_8): Linear(in_features=40, out_features=1, bias=True)
)
)

CPINN model (B,D,S)



CPINN model (B,D,S)

