In [ ]:
```python
import numpy as np
import torch as torch
import torch.nn as nn
import torch.nn.functional as F
import torch.optim as optim
import seaborn as sns
import pandas as pd
import matplotlib.pyplot as plt
from datetime import datetime
import random
from scipy.stats import norm

import os
import pathlib

from Model import *
from utils import *

torch.autograd.set_detect_anomaly(True)
start_time=datetime.now().strftime('%B %d - %H:%M:%S')
```

In [ ]:
```python
#Global parameters
GlobalParams1=Params(param_type='k1',target_type='indicator',trick='clamp',loss_type='MSELoss',delta=0.01,w=0.3,lr=0.0005)
dB1 = SampleBMIncr(GlobalParams=GlobalParams1)
init_x1 =  Sample_Init(GlobalParams=GlobalParams1)
init_c1= torch.zeros_like(init_x1)

GlobalParams2=Params(param_type='k2',target_type='indicator',trick='clamp',loss_type='MSELoss',delta=0.01,w=0.3,lr=0.0005)
dB2 = SampleBMIncr(GlobalParams=GlobalParams2)   ## TODO: same dB?????
init_x2 =  Sample_Init(GlobalParams=GlobalParams2)
init_c2= torch.zeros_like(init_x2)

NT1=GlobalParams1.NT1
NT2=GlobalParams1.NT2
dt=GlobalParams1.dt
device=GlobalParams1.device
learning_rate = GlobalParams1.lr

#Forward Loss
forward_losses = []

#How many batches
MaxBatch= 750

#How many optimization steps per batch
OptimSteps= 25

#Train on a single batch?
single_batch = True
```

```python
#Set up main models for y0 and z (z will be list of models)
v0_model_main1 = Network(scaler_type='minmax')
u0_model_main1 = Network(scaler_type='minmax')
y0_model_main1 = Network(scaler_type='minmax')

zv_models_main1 = [Network() for i in range(NT1)]
zu_models_main1 = [Network() for i in range(NT1)]
zy_models_main1 = [Network() for i in range(NT2)]
main_models1=Main_Models(GlobalParams=GlobalParams1)
main_models1.create(v0_model=v0_model_main1,
                    u0_model=u0_model_main1,
                    y0_model=y0_model_main1,
                    zv_models=zv_models_main1,
                    zu_models=zu_models_main1,
                    zy_models=zy_models_main1,
                    forward_loss=forward_losses,
                    dB=dB1,
                    init_x=init_x1,
                    init_c=init_c1)

v0_model_main2 = Network(scaler_type='minmax')
u0_model_main2 = Network(scaler_type='minmax')
y0_model_main2 = Network(scaler_type='minmax')

zv_models_main2 = [Network() for i in range(NT1)]
zu_models_main2 = [Network() for i in range(NT1)]
zy_models_main2 = [Network() for i in range(NT2)]
main_models2=Main_Models(GlobalParams=GlobalParams2)
main_models2.create(v0_model=v0_model_main2,
                    u0_model=u0_model_main2,
                    y0_model=y0_model_main2,
                    zv_models=zv_models_main2,
                    zu_models=zu_models_main2,
                    zy_models=zy_models_main2,
                    forward_loss=forward_losses,
                    dB=dB2,
                    init_x=init_x2,
                    init_c=init_c2)

pop1_dict={'dB':dB1,
           'init_x':init_x1 ,
           'init_c':init_c1 ,
           'GlobalParams':GlobalParams1,
           'main_models':main_models1}

pop2_dict={'dB':dB2,
           'init_x':init_x2 ,
           'init_c':init_c2 ,
           'GlobalParams':GlobalParams2,
           'main_models':main_models2}
```

In [ ]:

```
#Define optimization parameters
params=[]
params = list(main_models1.v0_model.parameters())+\
         list(main_models1.u0_model.parameters())+\
         list(main_models1.y0_model.parameters())+\
         list(main_models2.v0_model.parameters())+\
         list(main_models2.u0_model.parameters())+\
         list(main_models2.y0_model.parameters())
for i in range(NT1):
    params += list(main_models1.zv_models[i].parameters())
    params += list(main_models1.zu_models[i].parameters())
    params += list(main_models2.zv_models[i].parameters())
    params += list(main_models2.zu_models[i].parameters())

for i in range(NT2):
    params += list(main_models1.zy_models[i].parameters())
    params += list(main_models2.zy_models[i].parameters())

#Set up optimizer and scheduler
optimizer = optim.Adamax(params, lr=learning_rate)
scheduler = torch.optim.lr_scheduler.StepLR(optimizer, step_size=100, gamma=0.95)

for k in range(0,MaxBatch):

    print("Batch Number: ", k+1)
    sloss=0
    #optimize main network wrt the foward loss
    for l in range(0,OptimSteps):
        optimizer.zero_grad()
        loss = get_foward_loss(pop1_dict=pop1_dict, pop2_dict=pop2_dict)
        loss.backward()
        # torch.nn.utils.clip_grad_norm_(parameters=params,max_norm=0.7)
        optimizer.step()
        scheduler.step()
        nloss = loss.detach().numpy()
        sloss += nloss
        # print('OptimStep: '+ str(l+1))
        # print('forward_loss: ' + str(nloss))
    avgloss = sloss/OptimSteps
    print("Average Error Est: ", avgloss)
    forward_losses.append(avgloss)

    #Generate a new batch if using multiple batches
    if(not single_batch):

        dB1 = SampleBMIncr(GlobalParams=GlobalParams1)
        init_x1 =  Sample_Init(GlobalParams=GlobalParams1)
        init_c1= torch.zeros_like(init_x1)
        pop1_dict={'dB':dB1,
                'init_x':init_x1 ,
                'init_c':init_c1 ,
```

```
            'GlobalParams':GlobalParams1,
            'main_models':main_models1}

    dB2 = SampleBMIncr(GlobalParams=GlobalParams2)   ## TODO: same dB?????
    init_x2 =  Sample_Init(GlobalParams=GlobalParams2)
    init_c2= torch.zeros_like(init_x2)
    pop2_dict={'dB':dB2,
            'init_x':init_x2 ,
            'init_c':init_c2 ,
            'GlobalParams':GlobalParams2,
            'main_models':main_models2}
```

```
Batch Number:  511
Average Error Est:  0.25334512293338773
Batch Number:  512
Average Error Est:  0.2561871540546417
Batch Number:  513
Average Error Est:  0.2556095659732819
Batch Number:  514
Average Error Est:  0.2552836608886719
Batch Number:  515
Average Error Est:  0.2557710242271423
Batch Number:  516
Average Error Est:  0.25759397745132445
Batch Number:  517
Average Error Est:  0.2569338345527649
Batch Number:  518
Average Error Est:  0.2562114131450653
Batch Number:  519
Average Error Est:  0.25474767565727235
Batch Number:  520
Average Error Est:  0.2535404908657074
Batch Number:  521
Average Error Est:  0.25290215969085694
Batch Number:  522
Average Error Est:  0.2537191152572632
Batch Number:  523
Average Error Est:  0.25484328269958495
Batch Number:  524
Average Error Est:  0.2551500558853149
Batch Number:  525
Average Error Est:  0.2556950855255127
Batch Number:  526
Average Error Est:  0.2553786242008209
Batch Number:  527
Average Error Est:  0.2553538703918457
Batch Number:  528
Average Error Est:  0.25800718188285826
Batch Number:  529
Average Error Est:  0.25760679244995116
Batch Number:  530
Average Error Est:  0.2558461761474609
Batch Number:  531
Average Error Est:  0.2533164370059967
Batch Number:  532
Average Error Est:  0.25252642035484313
Batch Number:  533
Average Error Est:  0.25280941486358643
Batch Number:  534
Average Error Est:  0.2540713596343994
Batch Number:  535
Average Error Est:  0.25265707314014435
Batch Number:  536
```

```
Average Error Est:  0.2547719407081604
Batch Number:  537
Average Error Est:  0.2563394105434418
Batch Number:  538
Average Error Est:  0.2549392831325531
Batch Number:  539
Average Error Est:  0.256110405921936
Batch Number:  540
Average Error Est:  0.2564809823036194
Batch Number:  541
Average Error Est:  0.254546645283699
Batch Number:  542
Average Error Est:  0.2586342036724091
Batch Number:  543
Average Error Est:  0.255473473072052
Batch Number:  544
Average Error Est:  0.25343584060668944
Batch Number:  545
Average Error Est:  0.25242868542671204
Batch Number:  546
Average Error Est:  0.25407167613506315
Batch Number:  547
Average Error Est:  0.2530330717563629
Batch Number:  548
Average Error Est:  0.25331163287162783
Batch Number:  549
Average Error Est:  0.2539613556861877
Batch Number:  550
Average Error Est:  0.2538773429393768
Batch Number:  551
Average Error Est:  0.255934876203537
Batch Number:  552
Average Error Est:  0.2553553807735443
Batch Number:  553
Average Error Est:  0.2553675734996796
Batch Number:  554
Average Error Est:  0.2542779767513275
Batch Number:  555
Average Error Est:  0.2545525097846985
Batch Number:  556
Average Error Est:  0.2570012748241425
Batch Number:  557
Average Error Est:  0.25696077942848206
Batch Number:  558
Average Error Est:  0.2551564383506775
Batch Number:  559
Average Error Est:  0.25528382778167724
Batch Number:  560
Average Error Est:  0.2538026452064514
Batch Number:  561
Average Error Est:  0.2533358108997345
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```
Batch Number:  562
Average Error Est:  0.25389507472515105
Batch Number:  563
Average Error Est:  0.2534640693664551
Batch Number:  564
Average Error Est:  0.25284066796302795
Batch Number:  565
Average Error Est:  0.25302694976329804
Batch Number:  566
Average Error Est:  0.2541284567117691
Batch Number:  567
Average Error Est:  0.2542165625095367
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Average Error Est:  0.2527033442258835
Batch Number:  569
Average Error Est:  0.2555674505233765
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Average Error Est:  0.25541244745254515
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Average Error Est:  0.2558934509754181
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Average Error Est:  0.25573731899261476
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Average Error Est:  0.2547616684436798
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Average Error Est:  0.2549994897842407
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Average Error Est:  0.25541202664375307
Batch Number:  576
Average Error Est:  0.25572821736335755
Batch Number:  577
Average Error Est:  0.2563110542297363
Batch Number:  578
Average Error Est:  0.25331354439258574
Batch Number:  579
Average Error Est:  0.2531255519390106
Batch Number:  580
Average Error Est:  0.2540177541971207
Batch Number:  581
Average Error Est:  0.2548508417606354
Batch Number:  582
Average Error Est:  0.2556892442703247
Batch Number:  583
Average Error Est:  0.255054167509079
Batch Number:  584
Average Error Est:  0.2524458932876587
Batch Number:  585
Average Error Est:  0.25421329379081725
Batch Number:  586
Average Error Est:  0.25172052919864657
Batch Number:  587
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Average Error Est:  0.2559692633152008
Batch Number:  588
Average Error Est:  0.2567941701412201
Batch Number:  589
Average Error Est:  0.2575932610034943
Batch Number:  590
Average Error Est:  0.2558558070659637
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Average Error Est:  0.25670161485672
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Average Error Est:  0.2554991662502289
Batch Number:  593
Average Error Est:  0.25273815989494325
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Average Error Est:  0.25376816749572756
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Average Error Est:  0.25314328968524935
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Average Error Est:  0.253875150680542
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Average Error Est:  0.2527375829219818
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Average Error Est:  0.25403633534908293
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Average Error Est:  0.2537402278184891
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Average Error Est:  0.25347447335720064
Batch Number:  601
Average Error Est:  0.25301360309123994
Batch Number:  602
Average Error Est:  0.2522430473566055
Batch Number:  603
Average Error Est:  0.25378188729286194
Batch Number:  604
Average Error Est:  0.25338986575603484
Batch Number:  605
Average Error Est:  0.2546562790870667
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Average Error Est:  0.25493533492088316
Batch Number:  607
Average Error Est:  0.25515164494514464
Batch Number:  608
Average Error Est:  0.2552088963985443
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Average Error Est:  0.25583635926246645
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Average Error Est:  0.2560724532604218
Batch Number:  611
Average Error Est:  0.25598768711090086
Batch Number:  612
Average Error Est:  0.2550676667690277
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Batch Number:  613
Average Error Est:  0.25517536997795104
Batch Number:  614
Average Error Est:  0.25749318599700927
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Average Error Est:  0.2562087535858154
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Average Error Est:  0.2551526999473572
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Average Error Est:  0.2560314869880676
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Average Error Est:  0.25314399242401125
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Average Error Est:  0.2547058522701263
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Average Error Est:  0.2557481575012207
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Average Error Est:  0.25640094637870786
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Average Error Est:  0.25593570590019227
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Average Error Est:  0.25675166249275205
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Average Error Est:  0.25576825261116026
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Average Error Est:  0.25369230449199676
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Average Error Est:  0.2525328135490417
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Average Error Est:  0.2526226419210434
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Average Error Est:  0.2527490735054016
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Average Error Est:  0.25252395689487456
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Average Error Est:  0.25330214977264404
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Average Error Est:  0.25345705926418305
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Average Error Est:  0.2550823390483856
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Batch Number:  664
Average Error Est:  0.25569151997566225
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Average Error Est:  0.25548787593841554
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Average Error Est:  0.2550759398937225
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Average Error Est:  0.25601667642593384
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Average Error Est:  0.25609751224517824
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Average Error Est:  0.2560144579410553
Batch Number:  690
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Average Error Est:  0.25365702688694003
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Batch Number:  715
Average Error Est:  0.2535156911611557
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Average Error Est:  0.2554833853244782
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Batch Number:  719
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Average Error Est:  0.2565371561050415
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Average Error Est:  0.25753889441490174
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Batch Number:  728
Average Error Est:  0.2577917861938477
Batch Number:  729
Average Error Est:  0.2572092366218567
Batch Number:  730
Average Error Est:  0.2592224538326263
Batch Number:  731
Average Error Est:  0.2565219640731812
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Average Error Est:  0.2571061635017395
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Average Error Est:  0.25590378999710084
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Average Error Est:  0.2574273645877838
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Average Error Est:  0.2558604109287262
Batch Number:  737
Average Error Est:  0.2557777416706085
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Average Error Est:  0.25615055203437803
Batch Number:  739
Average Error Est:  0.2555123925209045
Batch Number:  740
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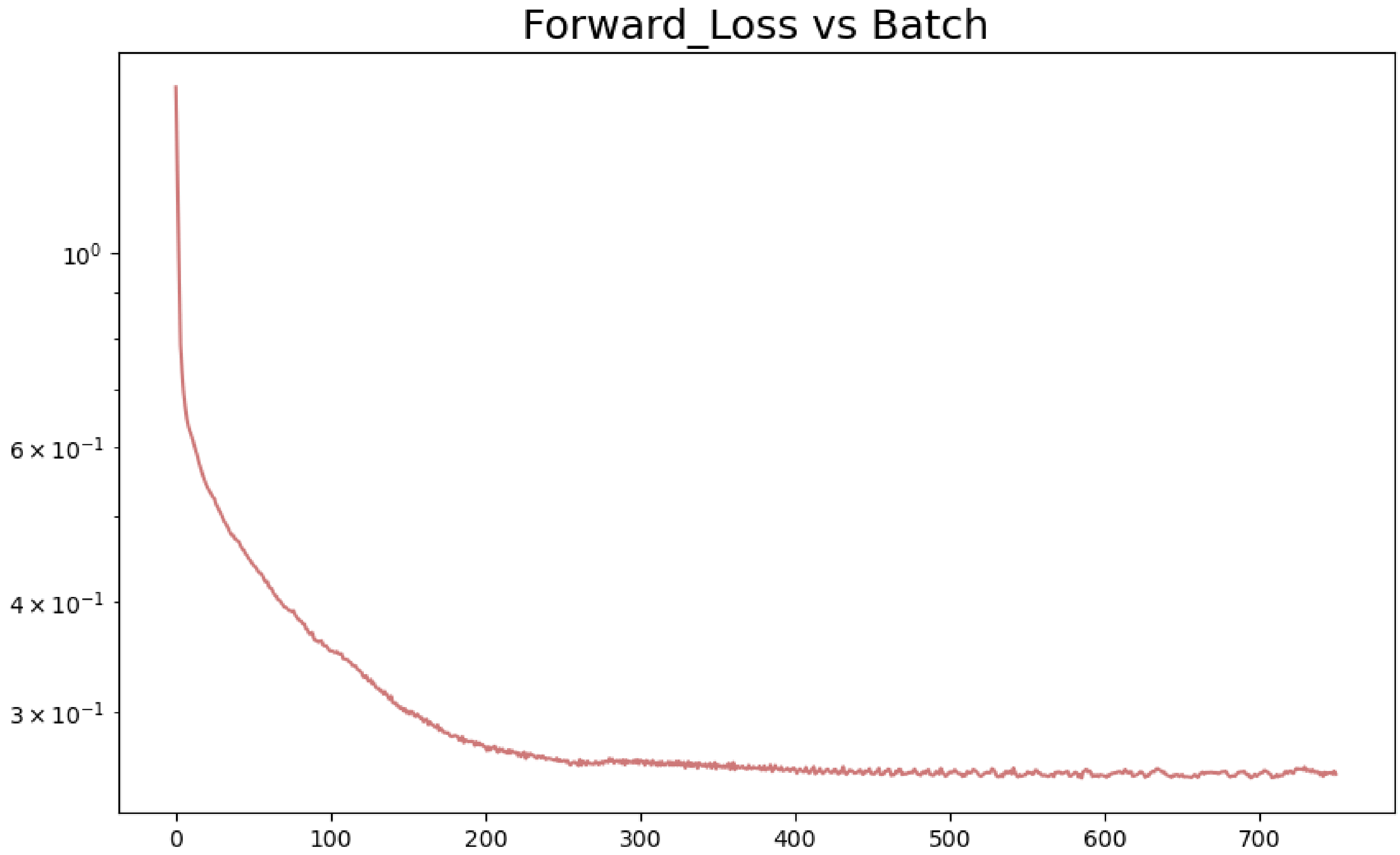
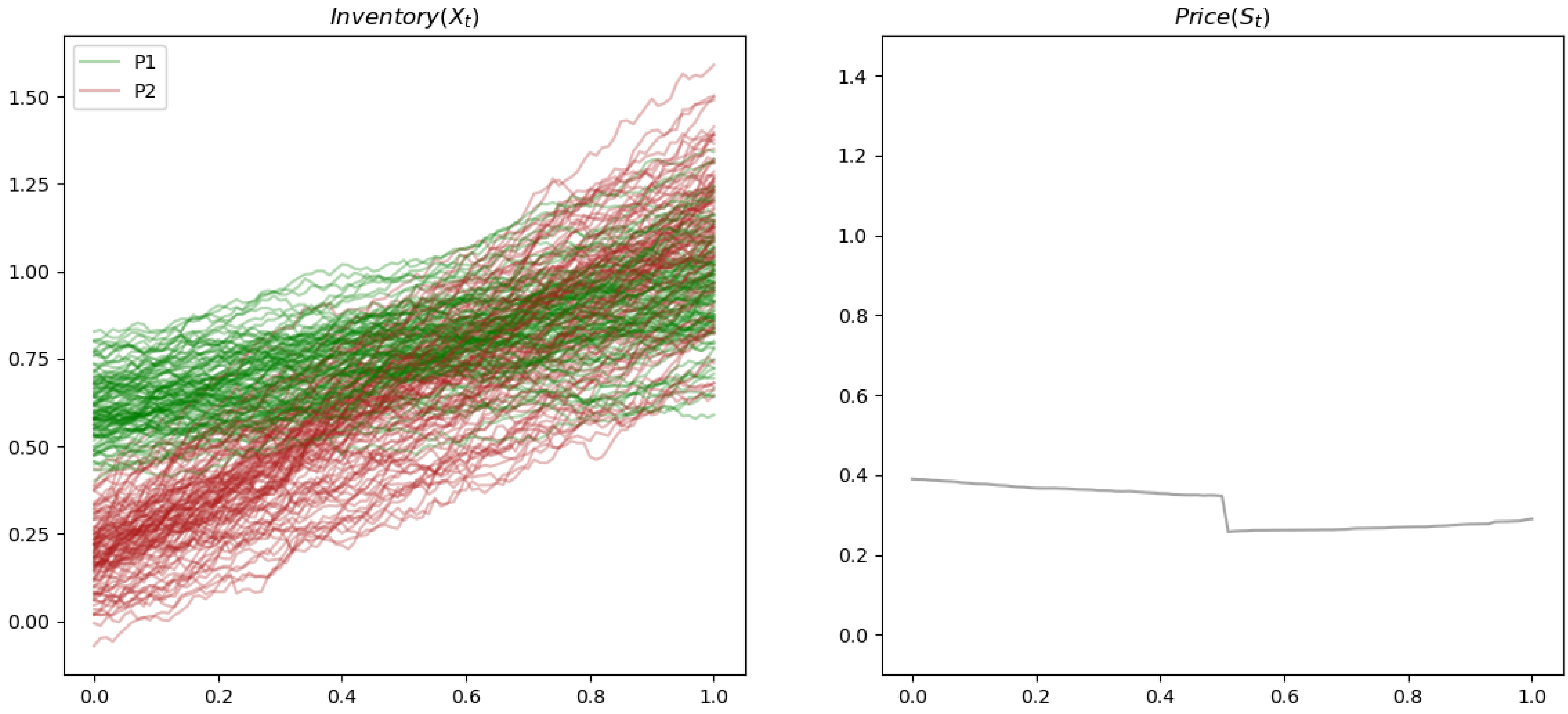
Average Error Est:  0.2537838590145111
Batch Number:  741
Average Error Est:  0.2552208244800568
Batch Number:  742
Average Error Est:  0.2529323983192444
Batch Number:  743
Average Error Est:  0.25561784029006956
Batch Number:  744
Average Error Est:  0.25423654973506926
Batch Number:  745
Average Error Est:  0.2551644837856293
Batch Number:  746
Average Error Est:  0.2552584230899811
Batch Number:  747
Average Error Est:  0.2554150629043579
Batch Number:  748
Average Error Est:  0.2543747538328171
Batch Number:  749
Average Error Est:  0.2564242315292358
Batch Number:  750
Average Error Est:  0.2543902909755707
```

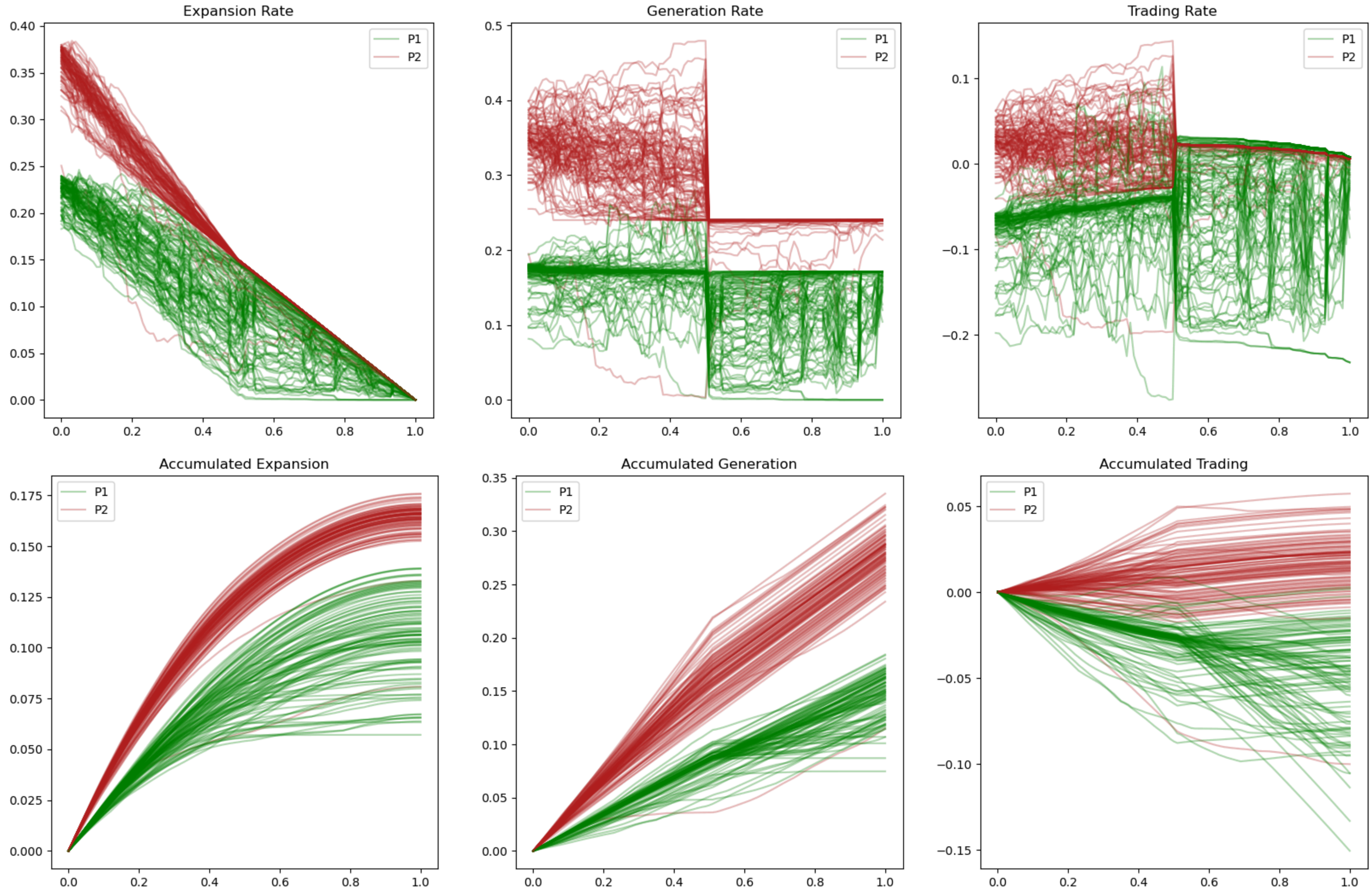
In [ ]:

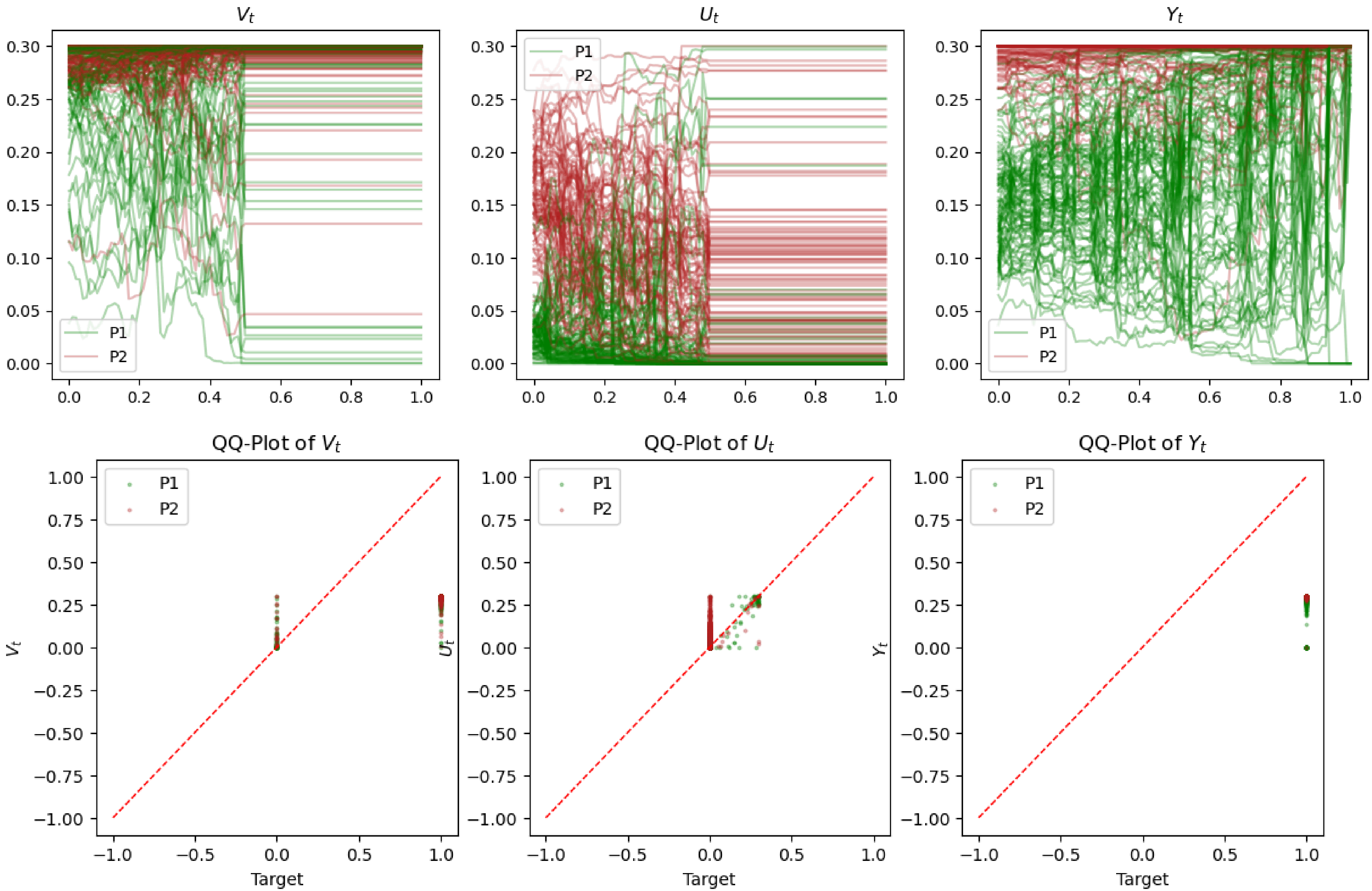
```
plot=plot_results(pop1_dict=pop1_dict, pop2_dict=pop2_dict, loss=forward_losses)
plot.FwdLoss(log=True)
plot.Inventory_And_Price()
plot.Decomposition_Inventory()
plot.Key_Processes()
plot.Terminal_Convergence()
```


Forward_Loss vs Batch
10^0
6×10^{-1}
4×10^{-1}
3×10^{-1}
0
100
200
300
400
500
600
700

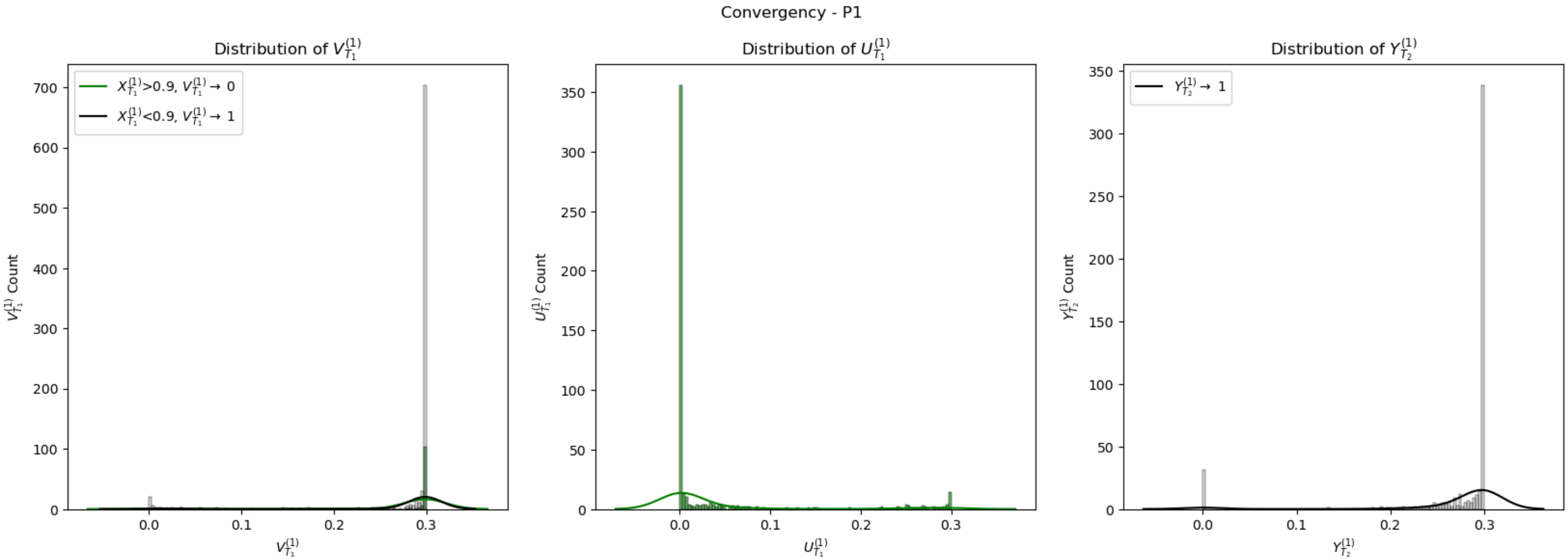


$Inventory(X_t)$
P1
P2
1.50
1.25
1.00
0.75
0.50
0.25
0.00
0.0
0.2
0.4
0.6
0.8
1.0
$Price(S_t)$
1.4
1.2
1.0
0.8
0.6
0.4
0.2
0.0
0.0
0.2
0.4
0.6
0.8
1.0

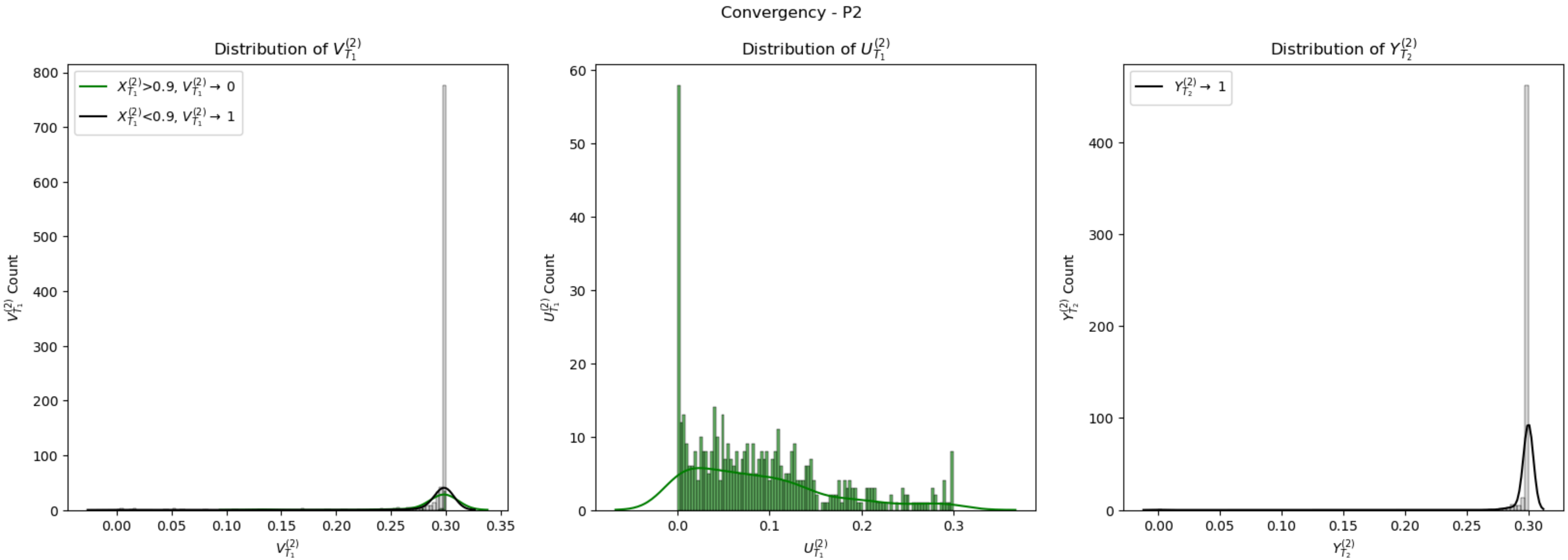

Expansion Rate
P1
P2
0.00
0.05
0.10
0.15
0.20
0.25
0.30
0.35
0.40
0.0
0.2
0.4
0.6
0.8
1.0
Generation Rate
P1
P2
0.0
0.1
0.2
0.3
0.4
0.5
0.0
0.2
0.4
0.6
0.8
1.0
Trading Rate
P1
P2
−0.2
−0.1
0.0
0.1
0.0
0.2
0.4
0.6
0.8
1.0
Accumulated Expansion
P1
P2
0.000
0.025
0.050
0.075
0.100
0.125
0.150
0.175
0.0
0.2
0.4
0.6
0.8
1.0
Accumulated Generation
P1
P2
0.00
0.05
0.10
0.15
0.20
0.25
0.30
0.35
0.0
0.2
0.4
0.6
0.8
1.0
Accumulated Trading
P1
P2
−0.15
−0.10
−0.05
0.00
0.05
0.0
0.2
0.4
0.6
0.8
1.0



V_t
U_t
Y_t
P1
P2
QQ-Plot of V_t
QQ-Plot of U_t
QQ-Plot of Y_t
Target



Convergency - P1
Distribution of $V_{T_1}^{(1)}$
$X_{T_1}^{(1)}$>0.9, $V_{T_1}^{(1)} \to 0$
$X_{T_1}^{(1)}$<0.9, $V_{T_1}^{(1)} \to 1$
$V_{T_1}^{(1)}$ Count
$V_{T_1}^{(1)}$
Distribution of $U_{T_1}^{(1)}$
$U_{T_1}^{(1)}$ Count
$U_{T_1}^{(1)}$
Distribution of $Y_{T_2}^{(1)}$
$Y_{T_2}^{(1)} \to 1$
$Y_{T_2}^{(1)}$ Count
$Y_{T_2}^{(1)}$



Convergency - P2
Distribution of $V_{T_1}^{(2)}$
$X_{T_1}^{(2)}$>0.9, $V_{T_1}^{(2)} \to 0$
$X_{T_1}^{(2)}$<0.9, $V_{T_1}^{(2)} \to 1$
$V_{T_1}^{(2)}$ Count
$V_{T_1}^{(2)}$
Distribution of $U_{T_1}^{(2)}$
$U_{T_1}^{(2)}$ Count
$U_{T_1}^{(2)}$
Distribution of $Y_{T_2}^{(2)}$
$Y_{T_2}^{(2)} \to 1$
$Y_{T_2}^{(2)}$ Count
$Y_{T_2}^{(2)}$

Save The Models

In [ ]:
```
print(f"{len(main_models1.loss)} steps\nStarted @ {start_time}\nSaved @ {datetime.now().strftime('%B %d - %H:%M:%S')}")   ## to examine whether
dir_path=pathlib.Path(os.getcwd(),
                      'Results',
                      'Best Models Saved',
                      'minmax_ind_0.0005lr_750steps_MSE_0.3w')
dir_path.mkdir()
path1=pathlib.Path(dir_path,'pop1.pt')
path2=pathlib.Path(dir_path,'pop2.pt')
main_models1.save_entire_models(path=path1)
main_models2.save_entire_models(path=path2)
```

```
750 steps
Started @ August 07 - 14:16:46
Saved @ August 07 - 20:54:36
```

Load The Model

In [ ]:
```
# # GlobalParams1=Params(param_type='k1',target_type='indicator',trick='clamp',loss_type='MSELoss',delta=0.03,K=0.9,lr=0.01)
# # GlobalParams2=Params(param_type='k2',target_type='indicator',trick='clamp',loss_type='MSELoss',delta=0.03,K=0.9,lr=0.01)
# models1=Main_Models(GlobalParams=GlobalParams1)
# models2=Main_Models(GlobalParams=GlobalParams2)
# path_dir=pathlib.Path(os.getcwd(),
#                       "Results",
#                       "Best Models Saved",
#                       'minmax_ind_0.01lr_300steps_MSE_1_dt')
# path1=pathlib.Path(path_dir,'pop1.pt')
# path2=pathlib.Path(path_dir,'pop2.pt')
# model_dict1=models1.load_entire_models(path=path1,overwrite=True)
# model_dict2=models2.load_entire_models(path=path2,overwrite=True)

# dB1=model_dict1['dB']
# init_x1=model_dict1['init_x']
# init_c1=model_dict1['init_c']
# pop1_dict= {'dB':dB1,
#             'init_x':init_x1 ,
#             'init_c':init_c1 ,
#             'GlobalParams':GlobalParams1,
#             'main_models':models1}

# dB2=model_dict2['dB']
# init_x2=model_dict2['init_x']
# init_c2=model_dict2['init_c']

# pop2_dict= {'dB':dB2,
#             'init_x':init_x2 ,
#             'init_c':init_c2 ,
```

```
#             'GlobalParams':GlobalParams2,
#             'main_models':models2}
# dt=GlobalParams1.dt
# NT1=GlobalParams1.NT1
# NT2=GlobalParams1.NT2
# NumTrain=GlobalParams1.NumTrain
# K=GlobalParams1.K
# loss=models1.loss

# plot=plot_results(pop1_dict=pop1_dict, pop2_dict=pop2_dict, loss=loss)
# plot.FwdLoss(log=True)
# plot.Inventory_And_Price()
# plot.Decomposition_Inventory()
# plot.Key_Processes()
# # plot.Terminal_Convergence()
```

In [ ]:

```
```