

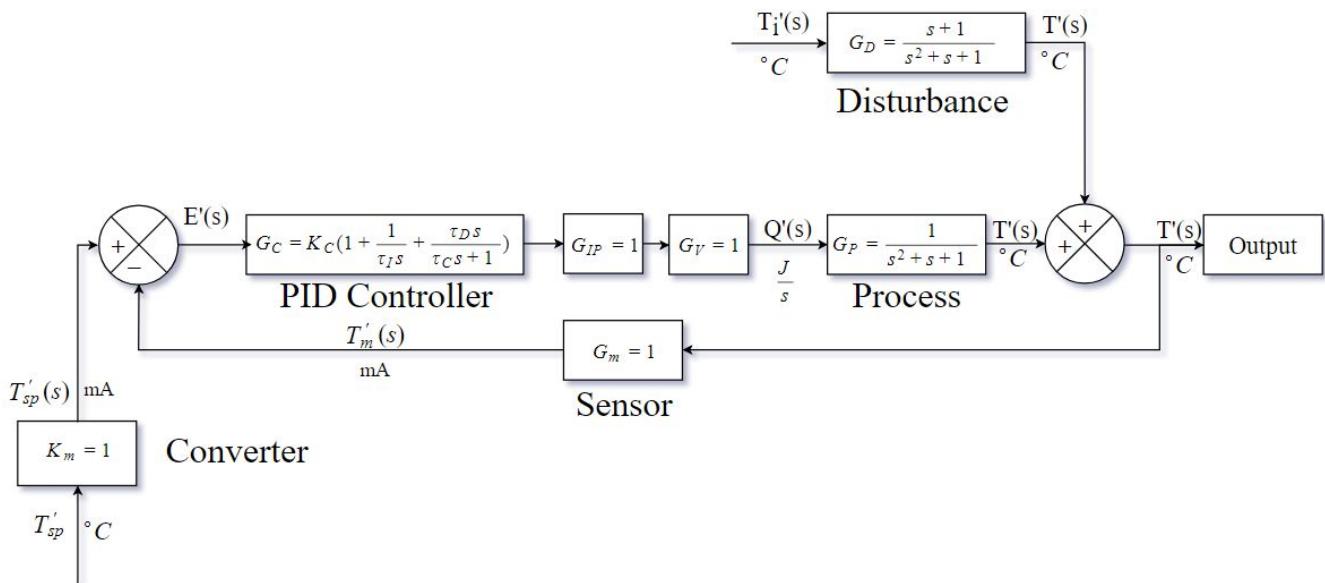
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If the performance metric is defined as a function of the parameters, “ $P(K_C, \tau_I, \tau_D, \tau_C)$,” then it is not a smooth one. Any given four-coordinate point is surrounded by countless local minima, such that gradient-based minimization of P changes neither P nor the parameters significantly. The more effective approach is a random search (*random_search.ipynb*, pages A38, A44) where the parameters are varied uniformly on a logarithmic scale and used to evaluate P .

To improve the search, several univariate trials are performed (changing one variable while others are held constant). While P oscillates very rapidly when any parameter is smoothly adjusted, it shows a general positive correlation with K_C (capped at 10000) and a negative correlation with τ_I . The search is narrowed to the most successful regions with respect to each variable, keeping the results of the tests in mind: K_C is constrained to the interval [1000, 10000]; τ_I to [0.0001, 0.001], τ_D to [0.05, 1.5], and τ_C to [0.0005, 0.1]. The narrow region can be searched more thoroughly than a wide region. Lower values of τ_I cannot not be tested because they frequently flag errors in “control.forced_response” due to the controller volatility they cause.

The minimum performance metric obtained is **6.603490145150944** using the parameters $(K_C, \tau_I, \tau_D, \tau_C) = (5688.814947611792, 0.0002280222206125743, 0.4941522520819933, 0.006245557968152839)$.

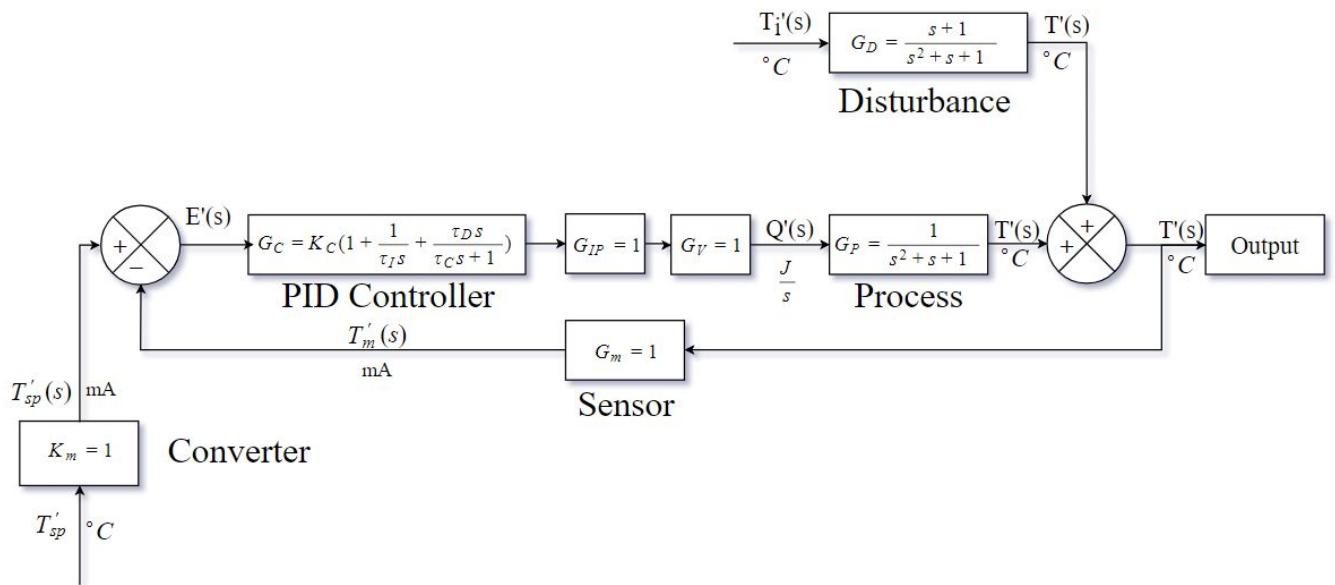
The simplest way of simulating a controller is with transfer functions: mathematical functions that describe a component within a system. They are commonly defined as the ratio between the output and input of the component in the frequency (s) domain, and are generally obtained by modelling the system, and then using the Laplace Transform to obtain the function in the s-domain. The relevant transfer functions were given in this assignment, as was the disturbance profile used. The inputs were processed into outputs using the G_{Total} function described in A40, and the difference between the setpoint and system output (i.e. $T_{SP} - T$) was passed through G_C (page A40) to obtain the new input. Python’s Control Systems library was used throughout to define and use the transfer functions (pages A40, A41, A44).

The results are checked using the *Verify_(Yankai).ipynb* code (pages A38, A39) to evaluate the performance metric for each disturbance profile using “control.forced_response” and return the average of the one hundred performance metrics. *Skeleton_(Masterplan_for_plots).ipynb* (pages A38, A41) performs the same calculations, plotting the data as it is generated.

Appendix: Figures, Plots, and Codes

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CV, MV, DV Plots (All 100 Profiles)	A3
Performance Metric Plot	A37
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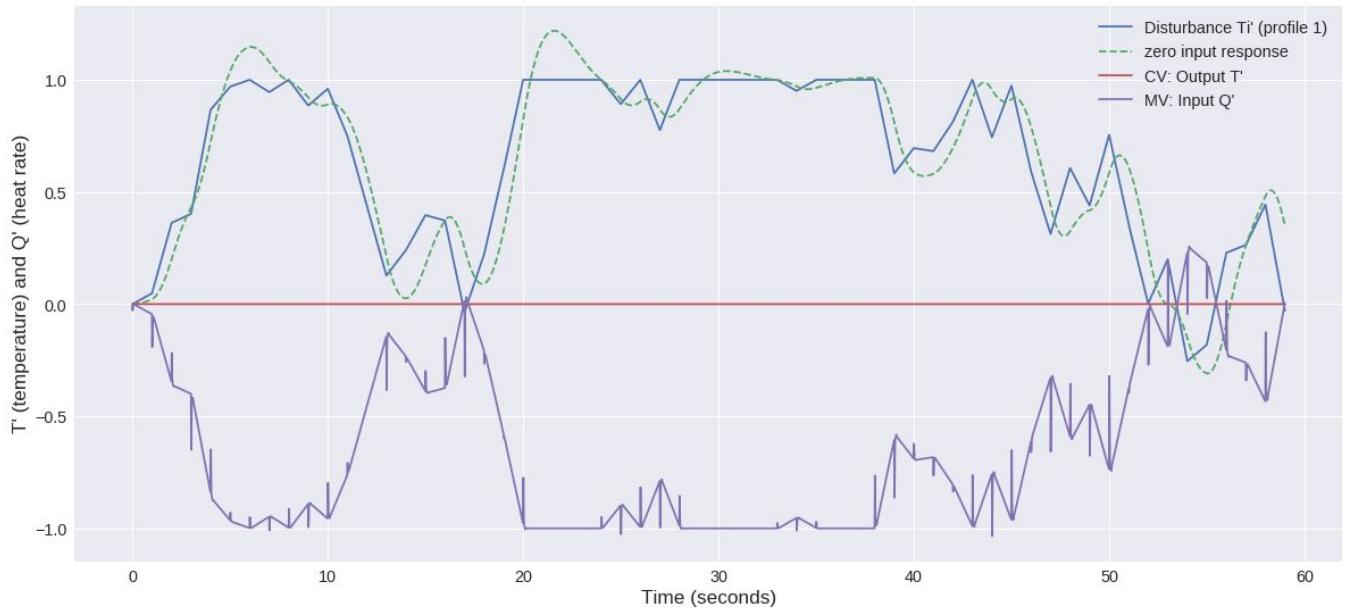
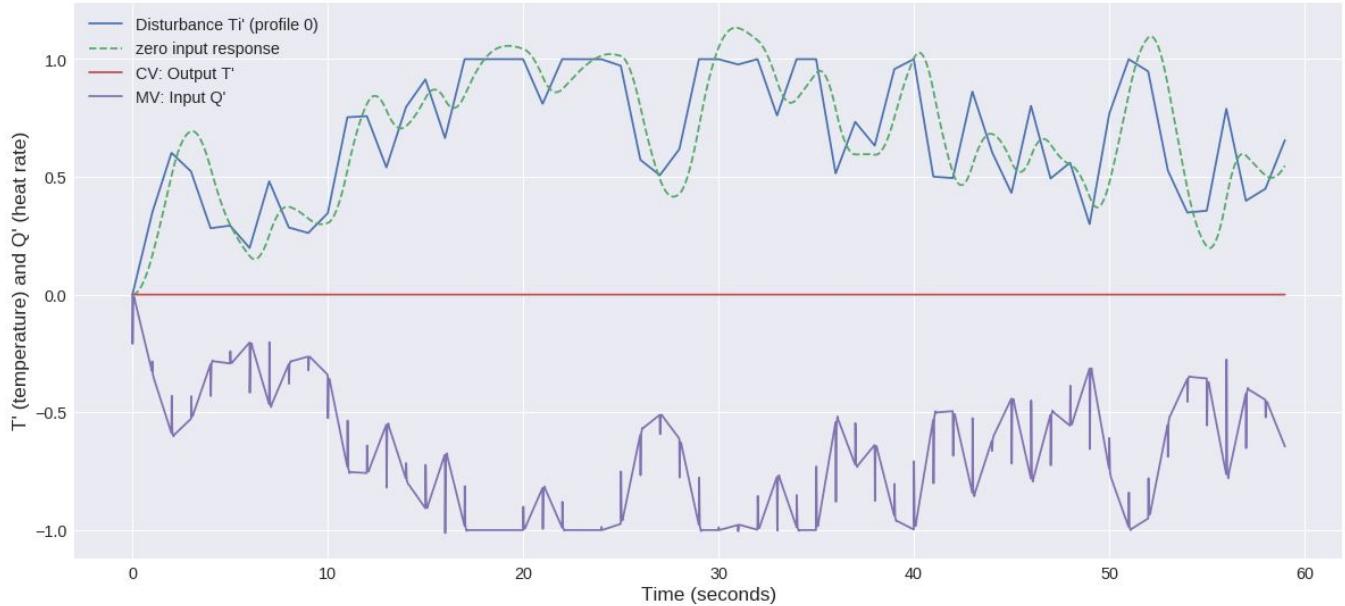
Block Diagram

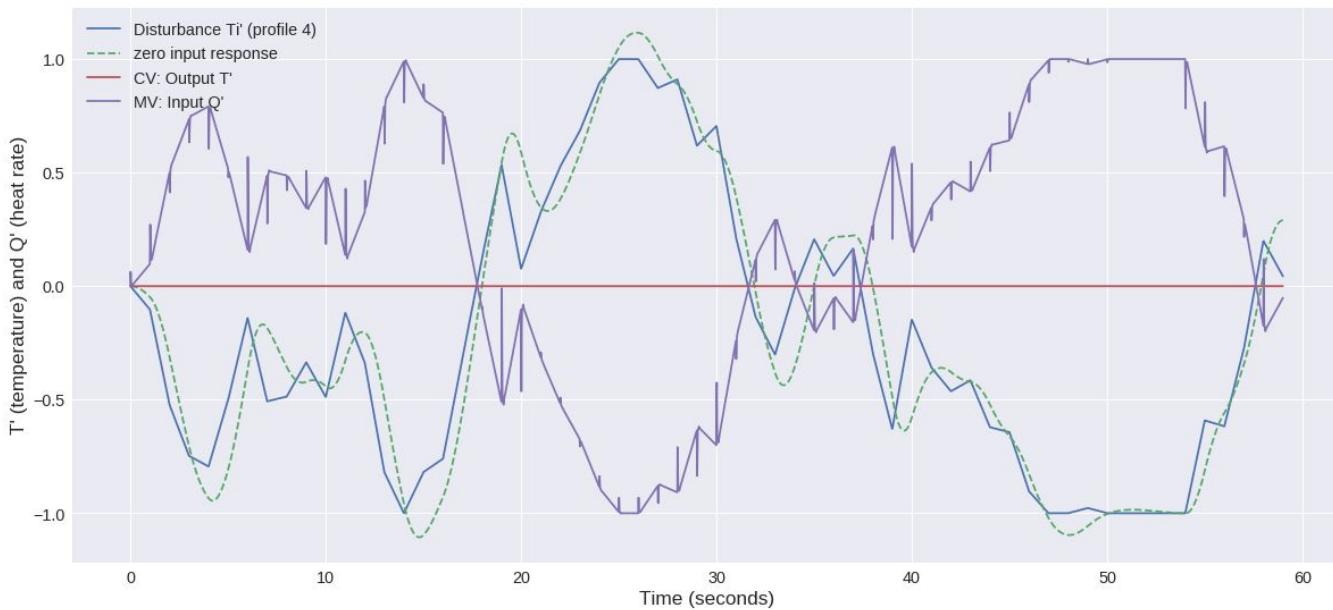
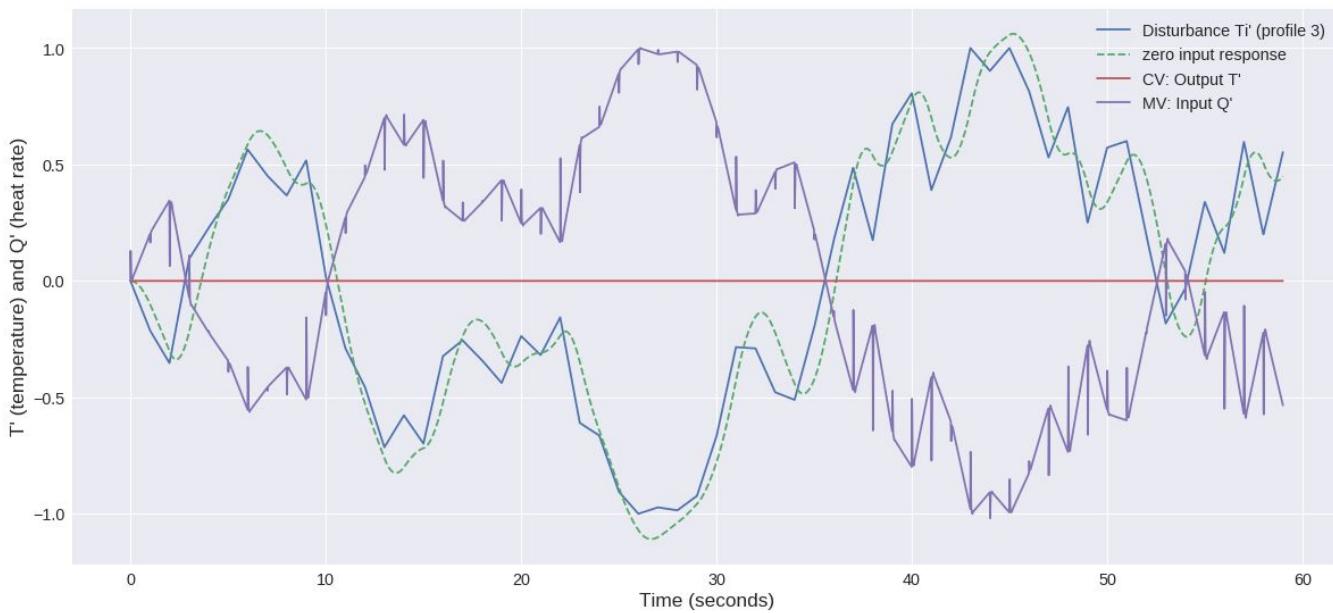
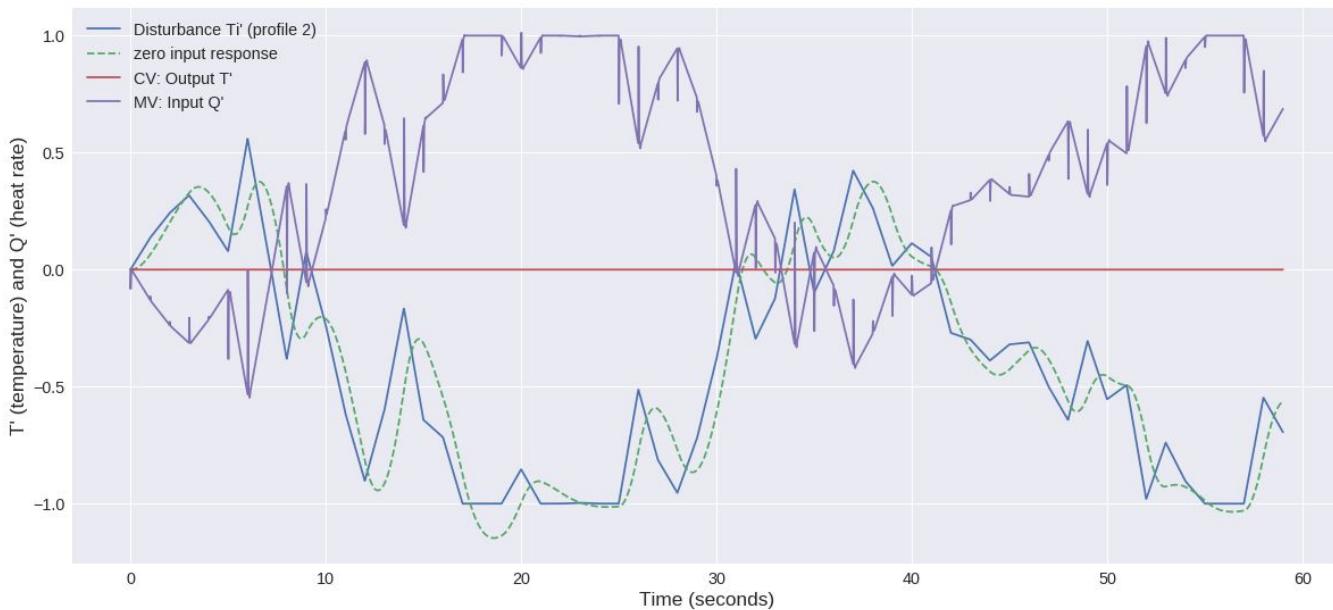


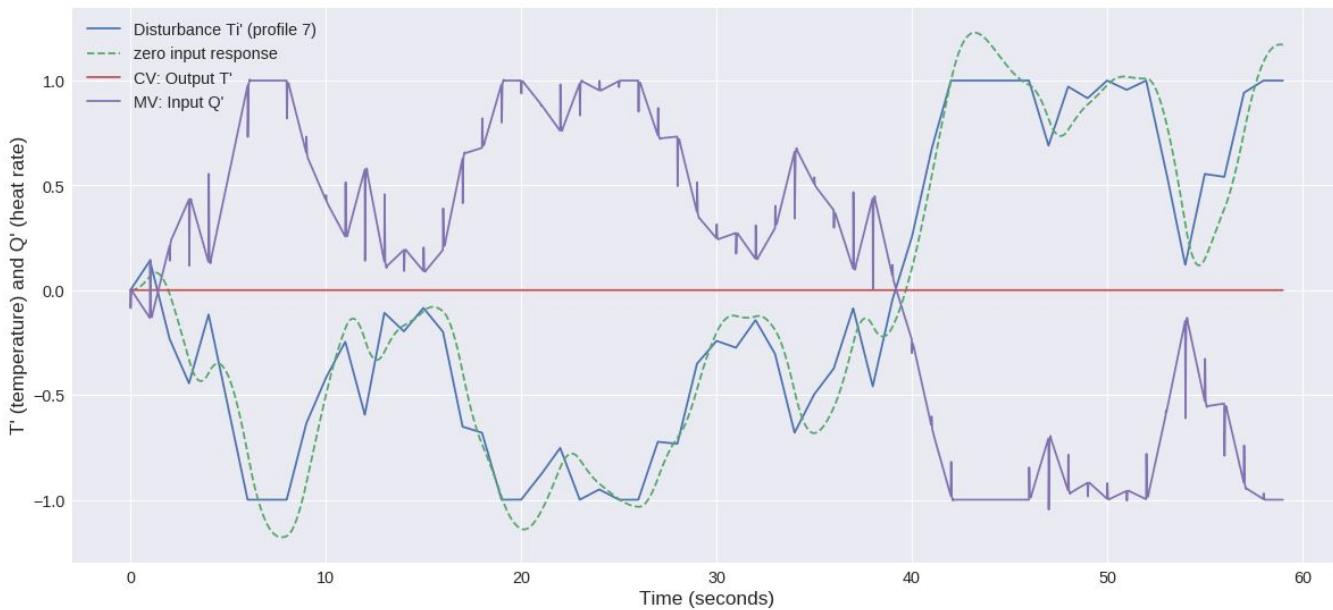
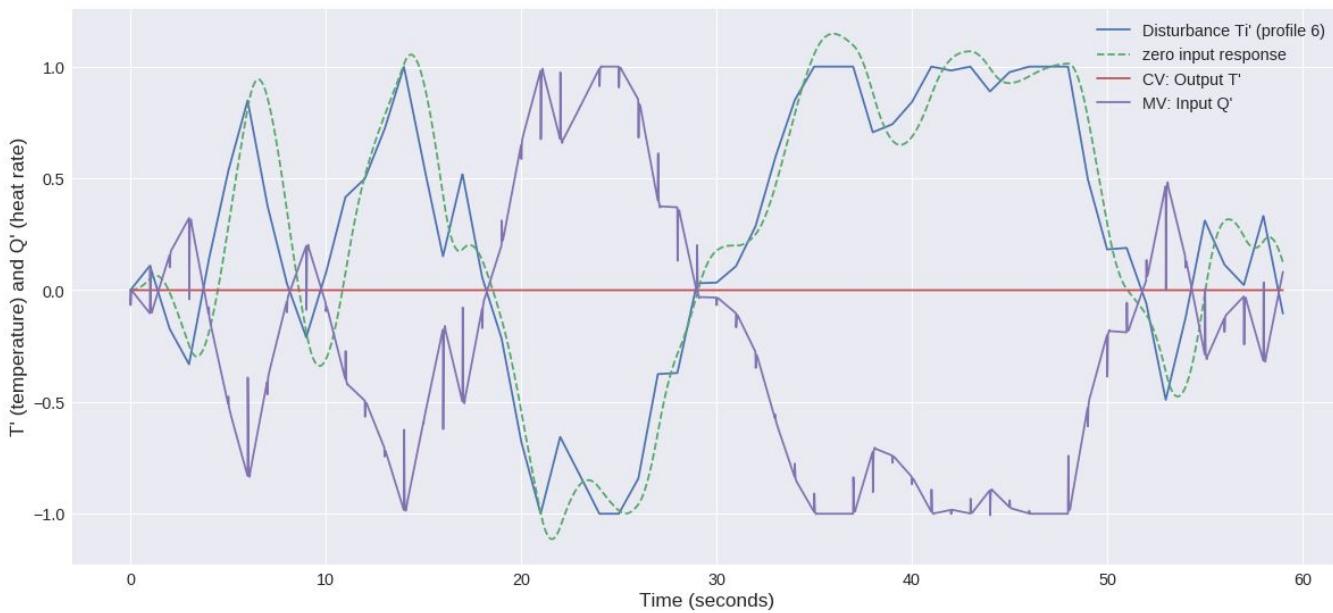
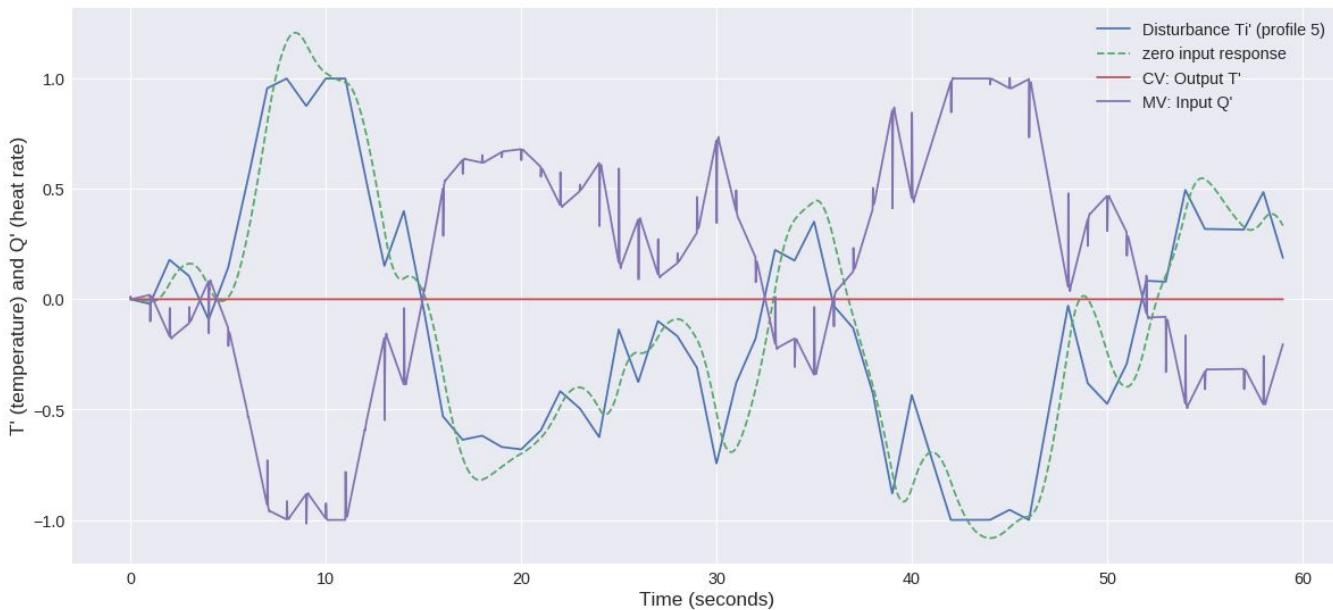
Controlled variable (red) and Manipulated variable (purple) plots:

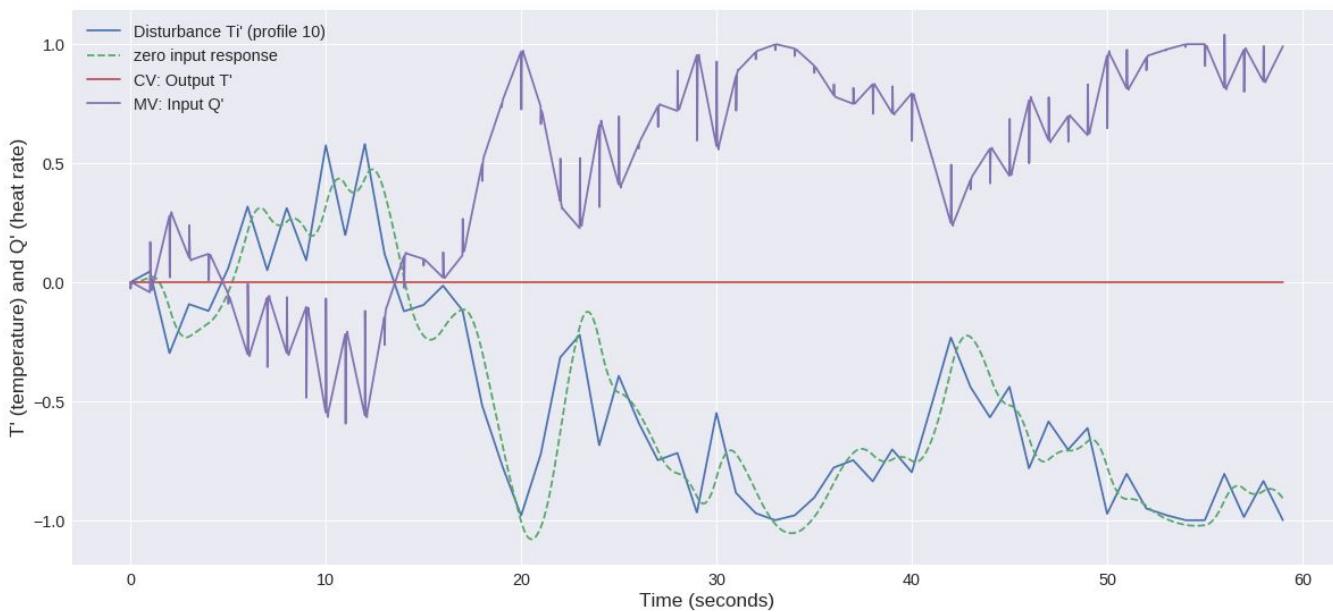
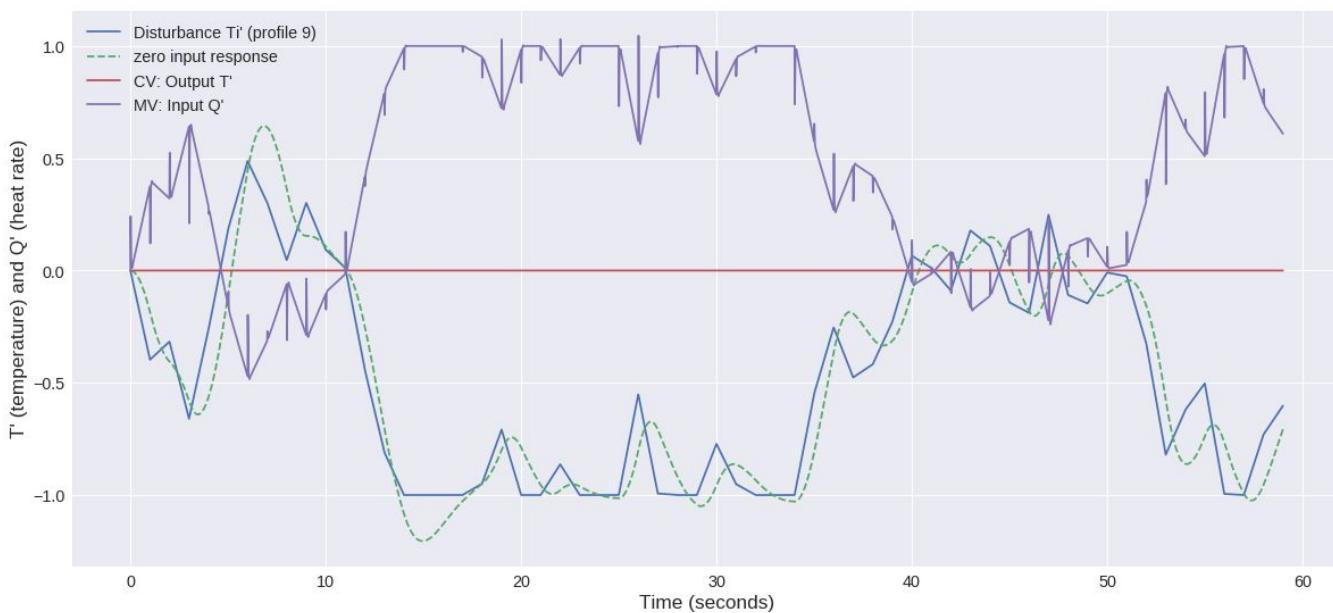
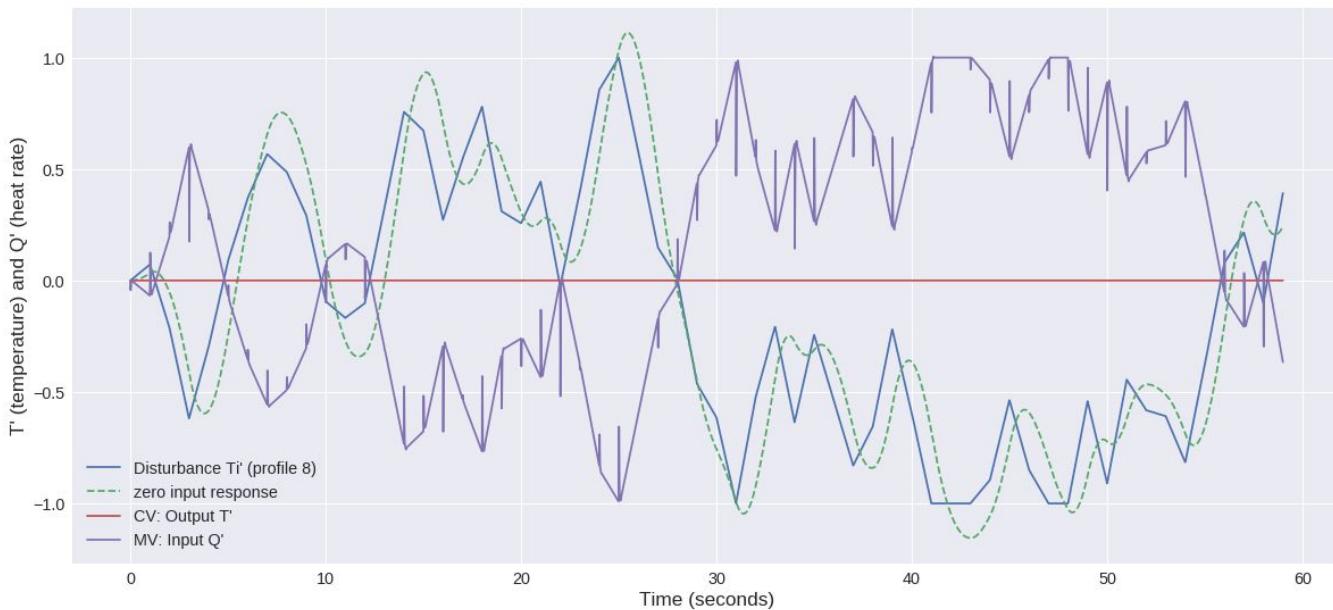
With high KC and low Tau values, the controller theoretically responds very quickly. Because of this, the input mirrors the output quite closely.

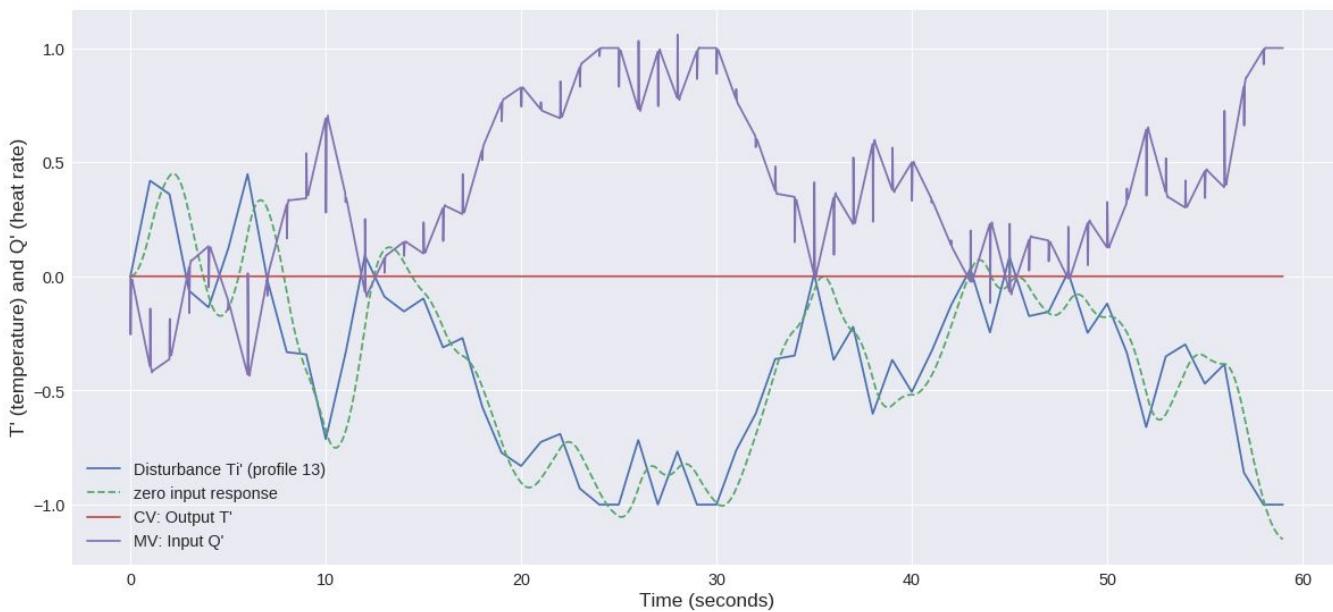
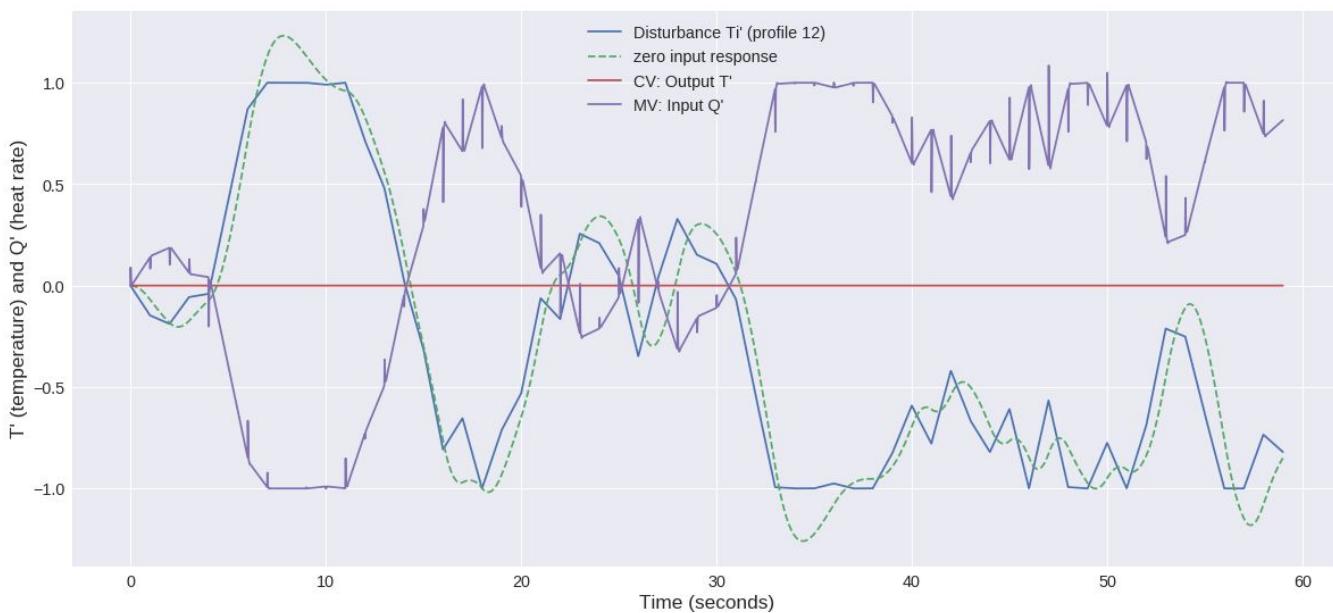
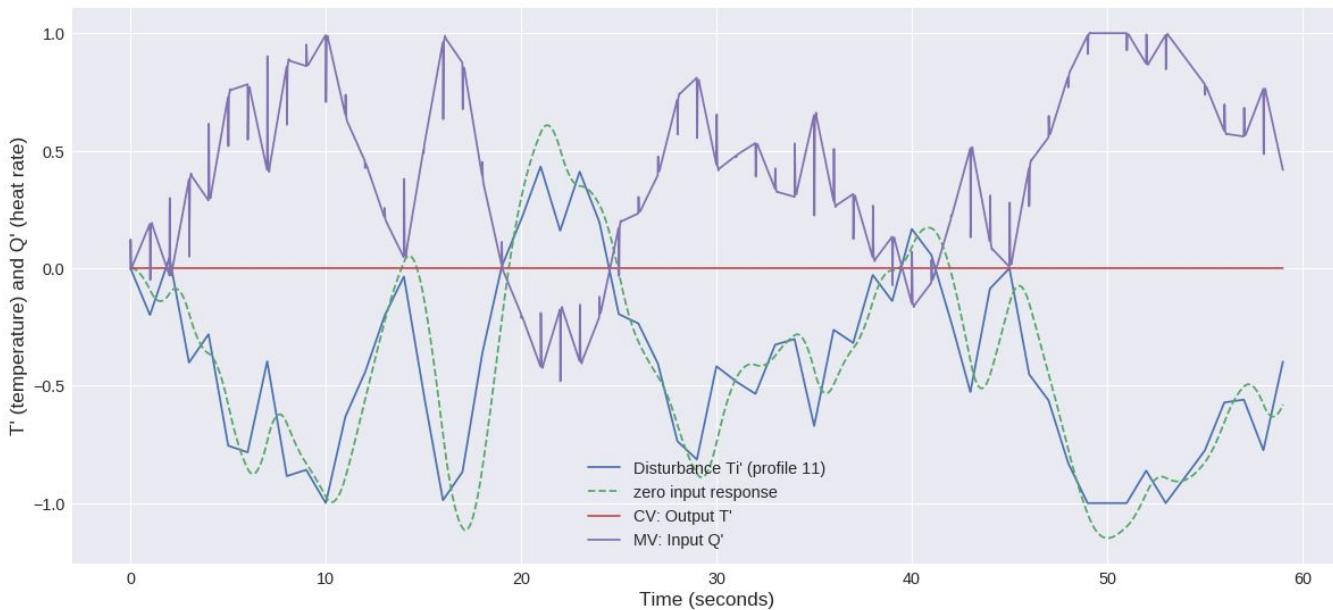
Plots are given in order, starting with Profile 0:

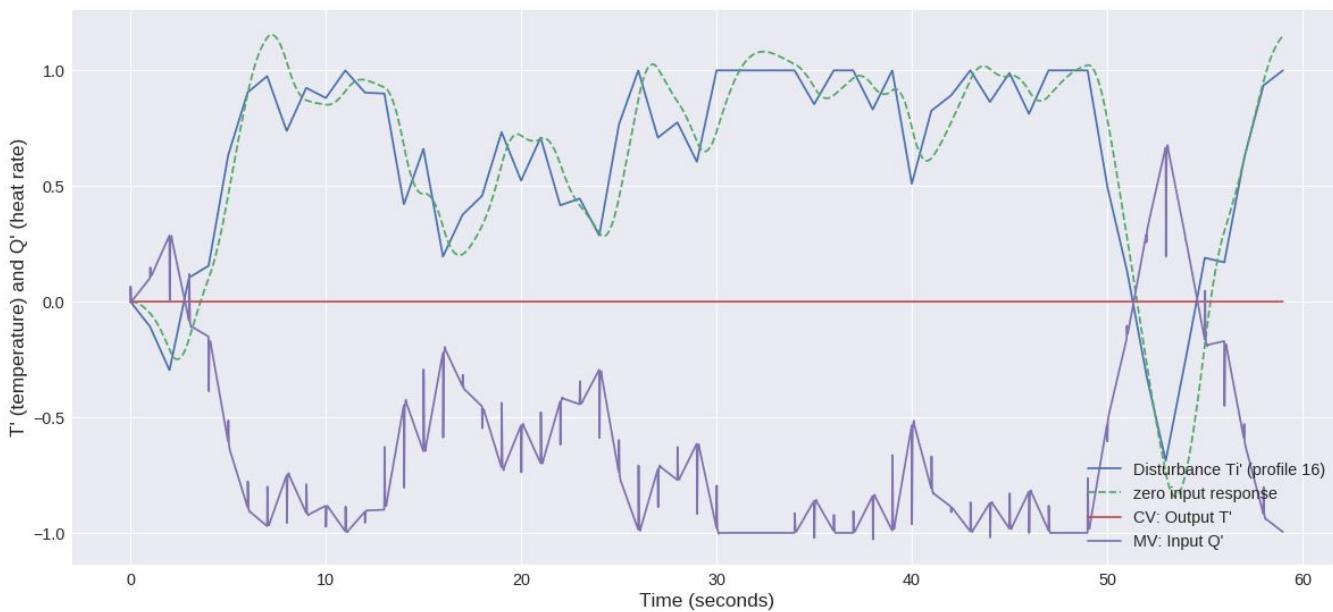
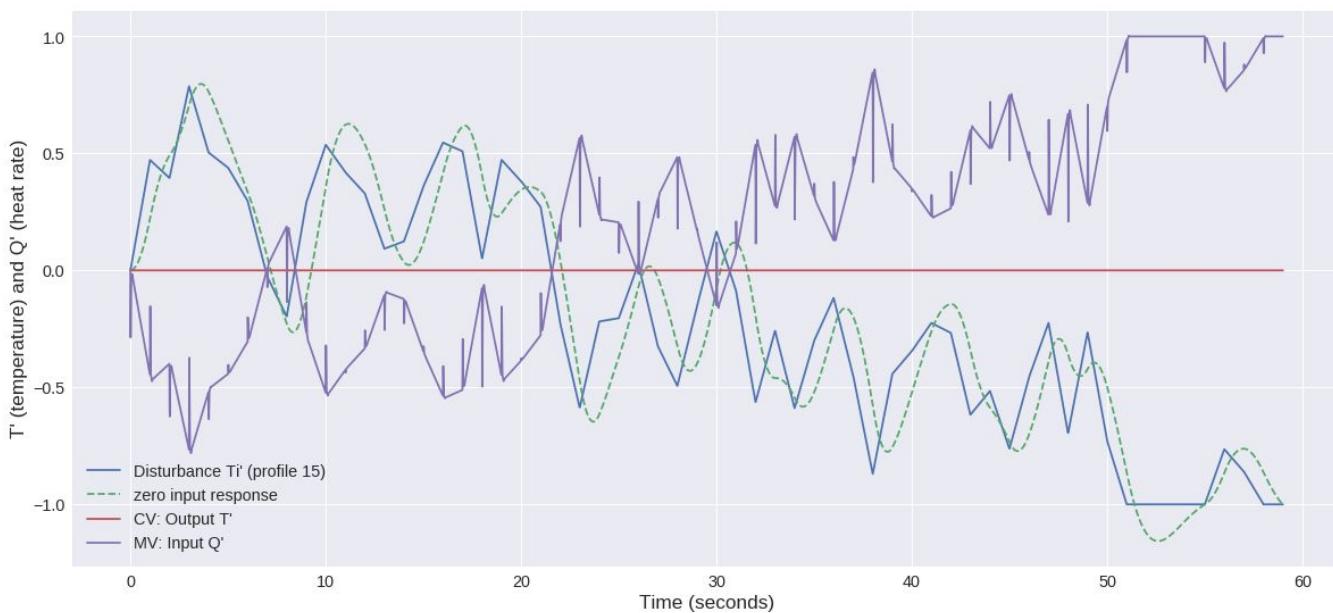
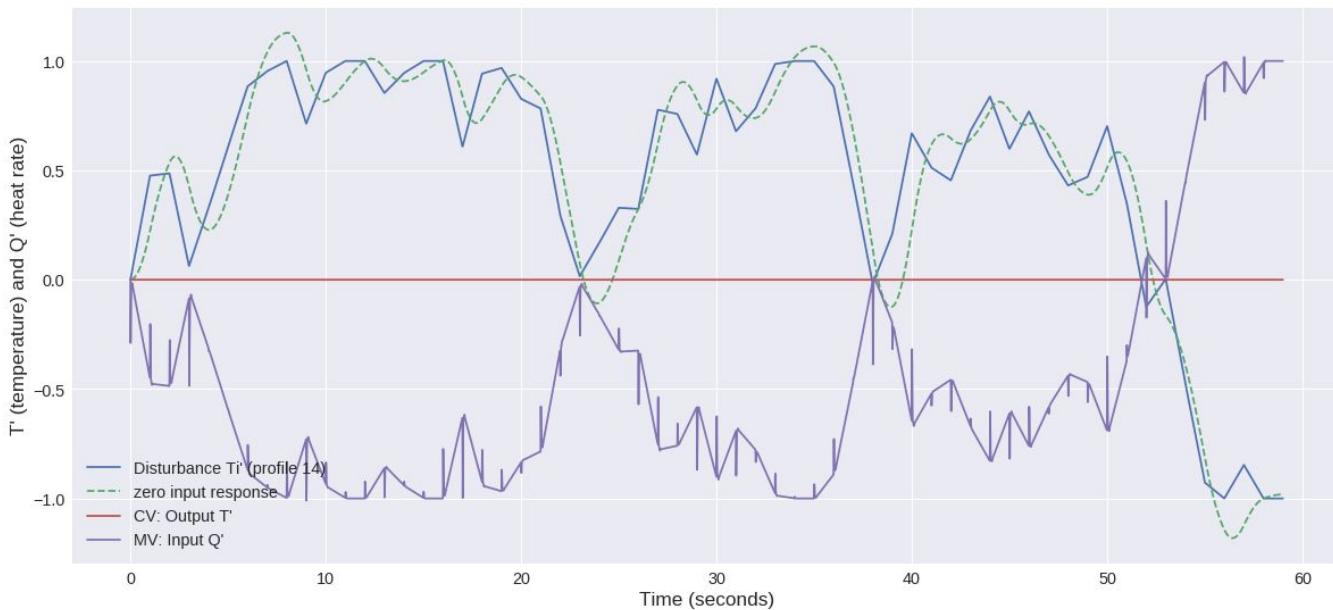


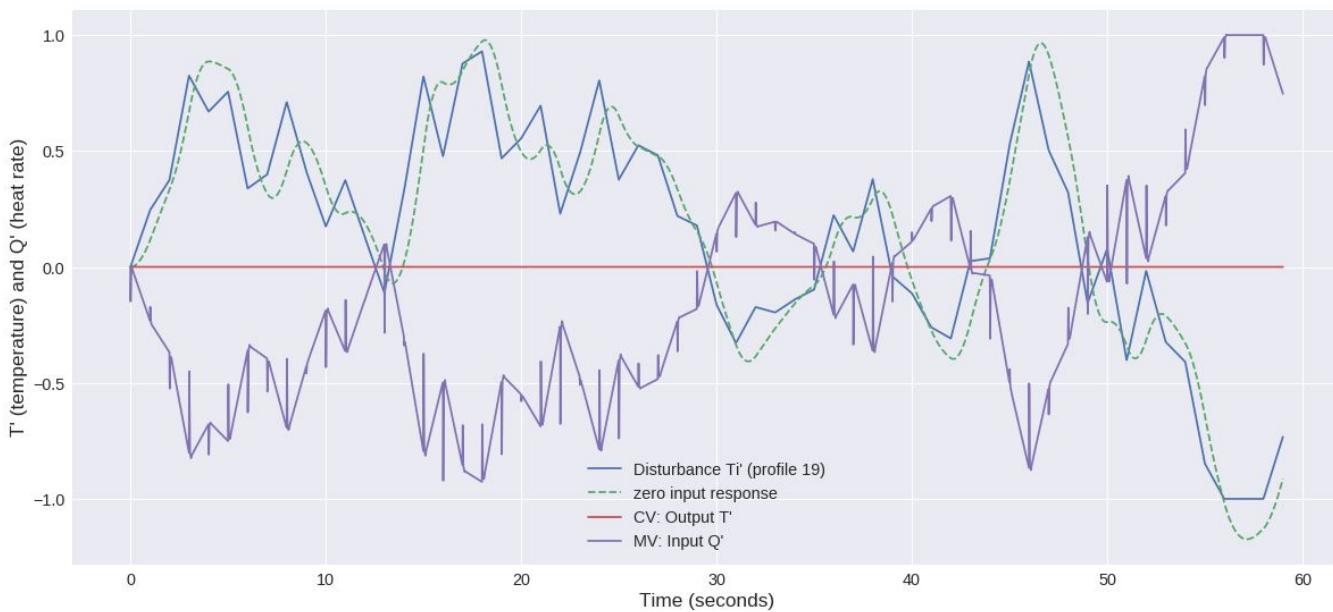
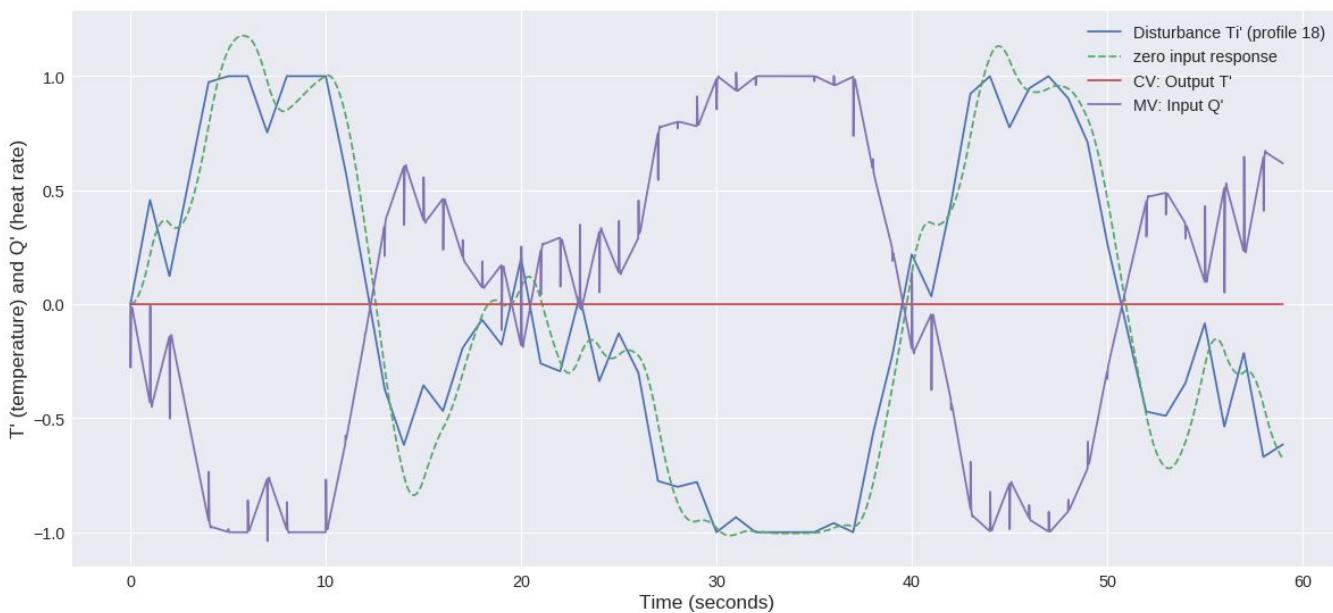
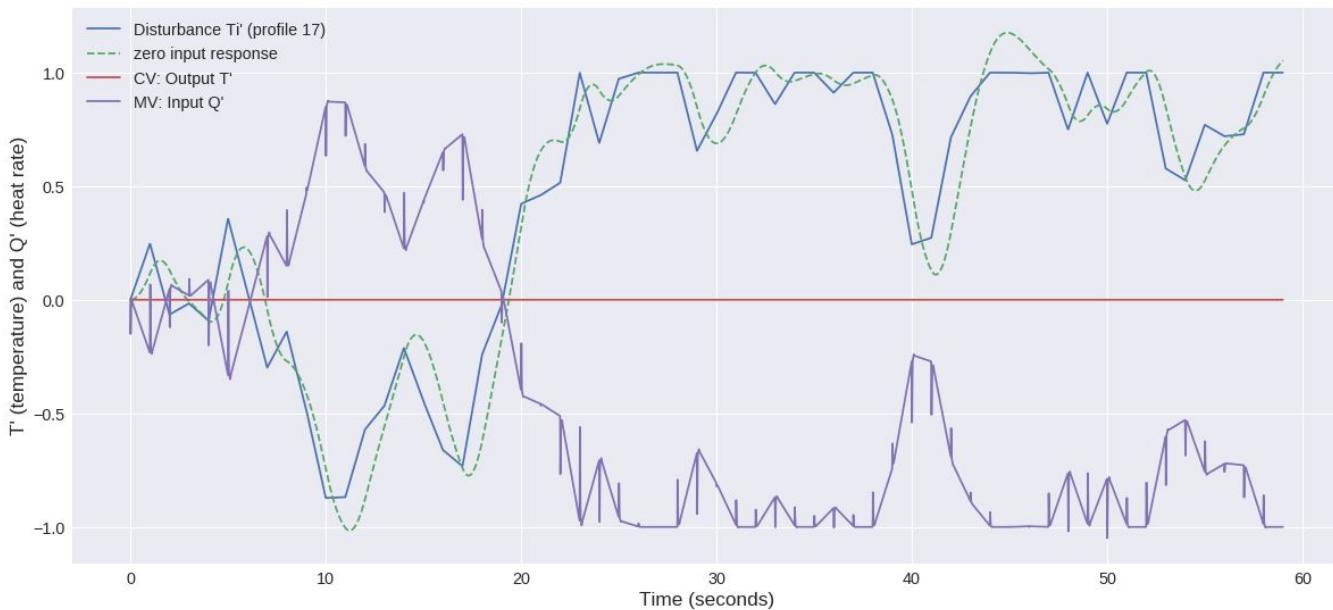


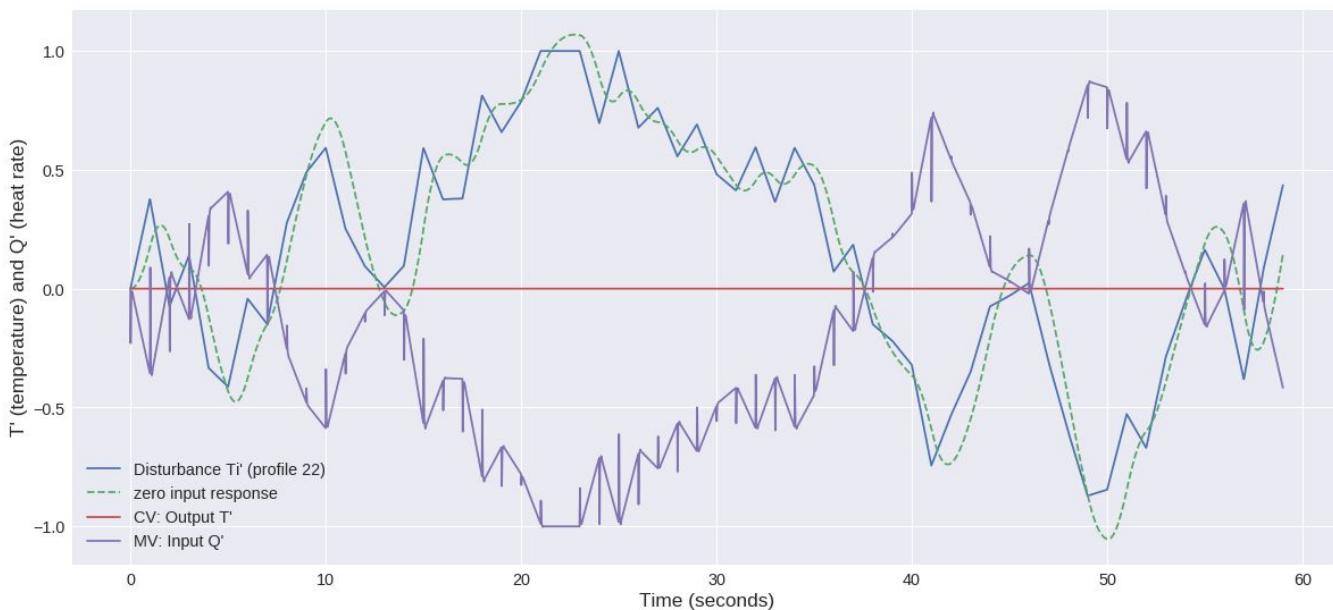
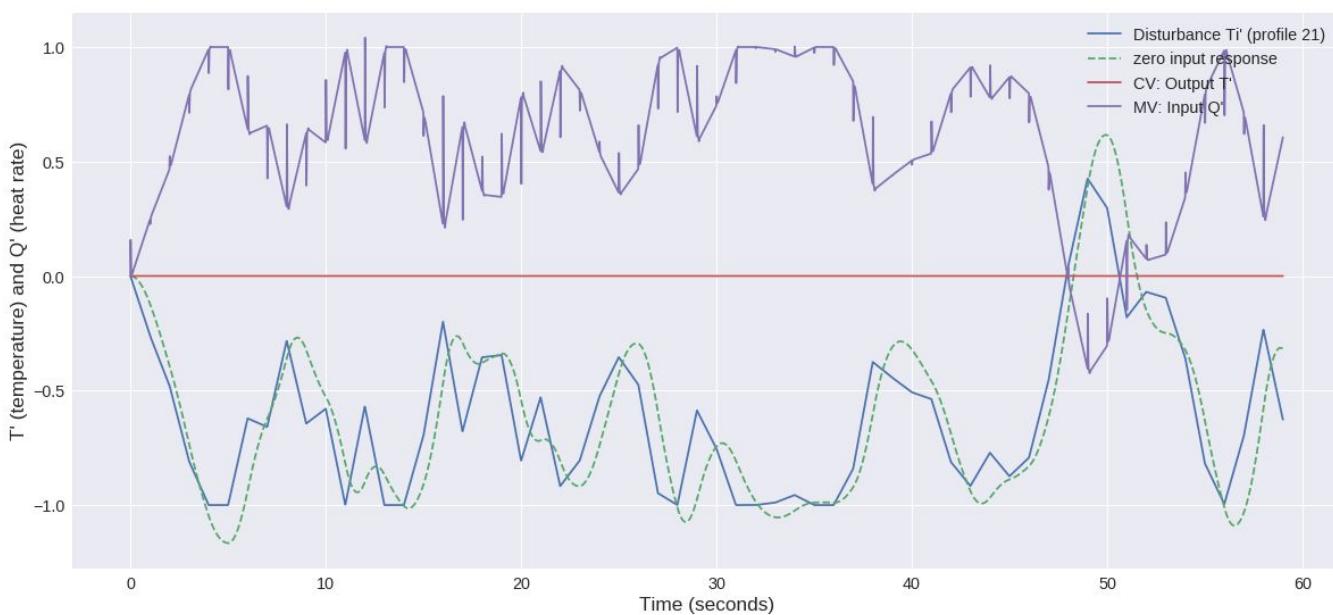
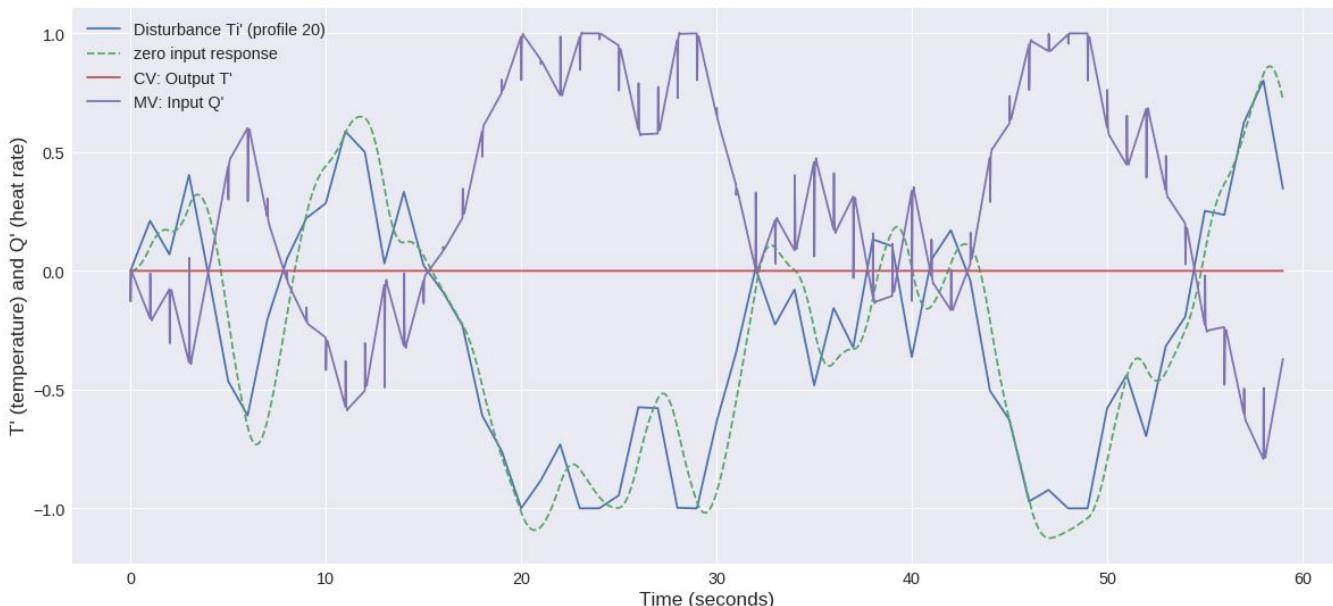


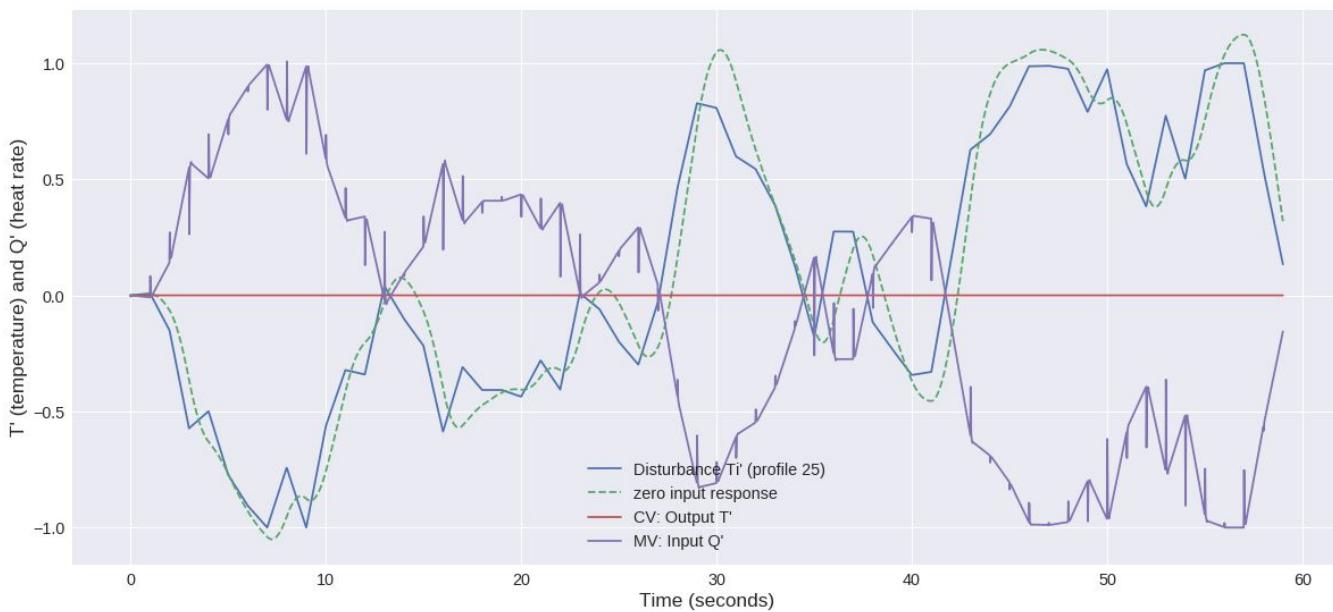
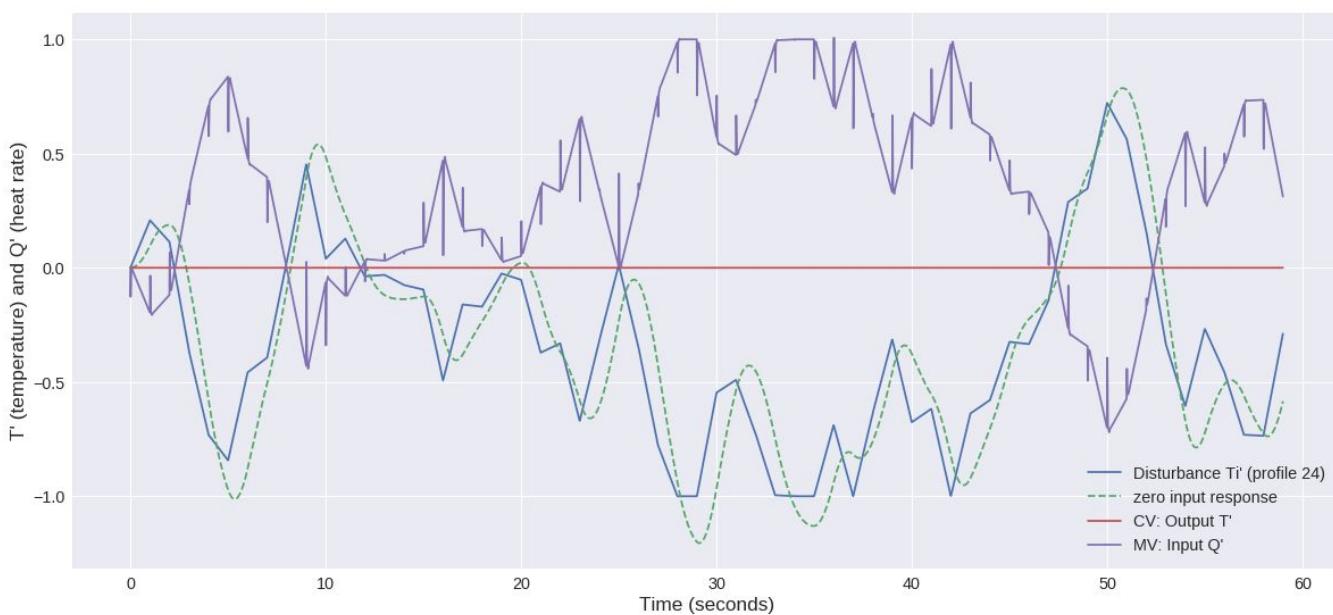
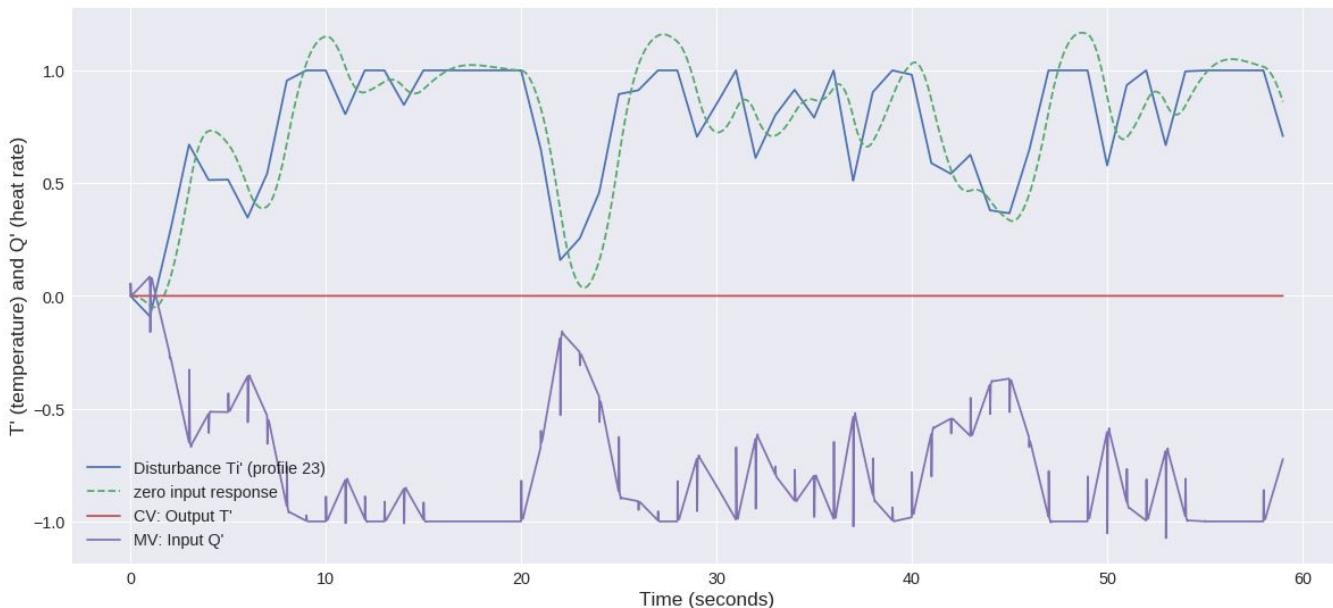


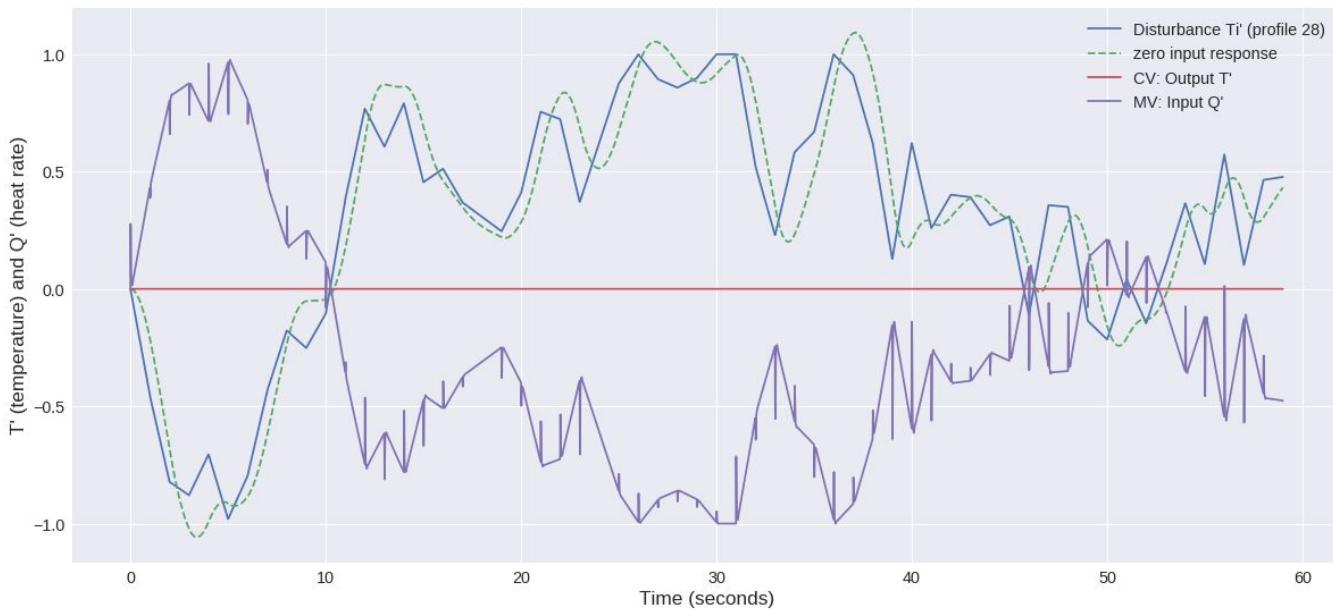
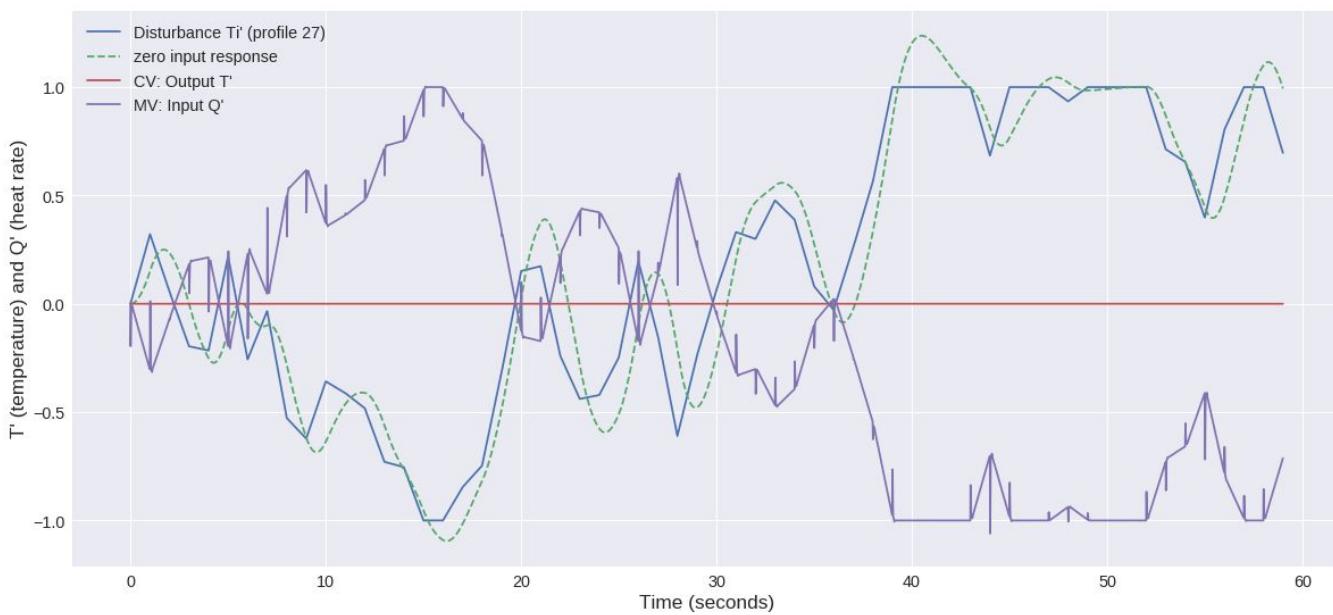
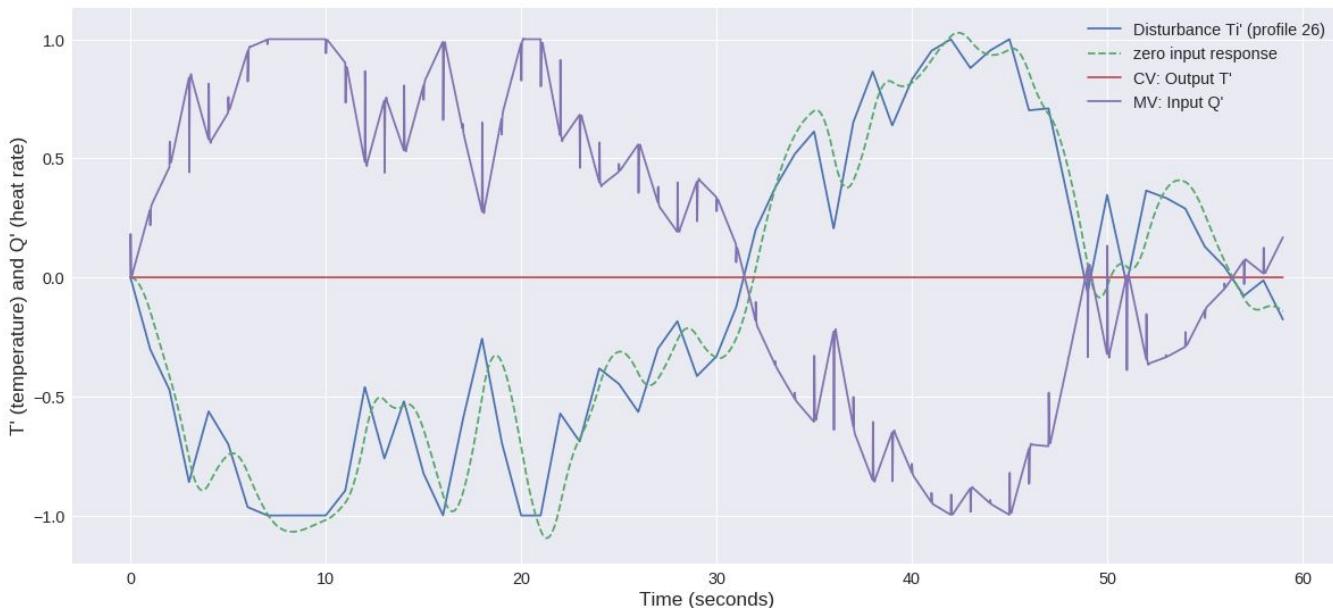


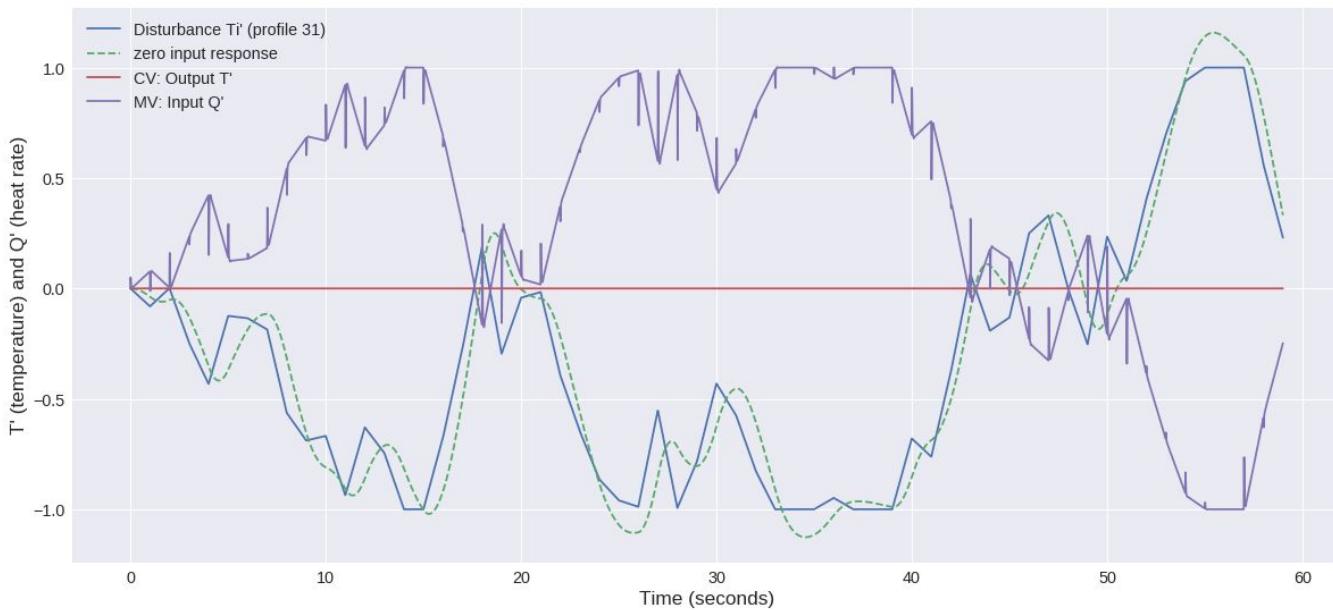
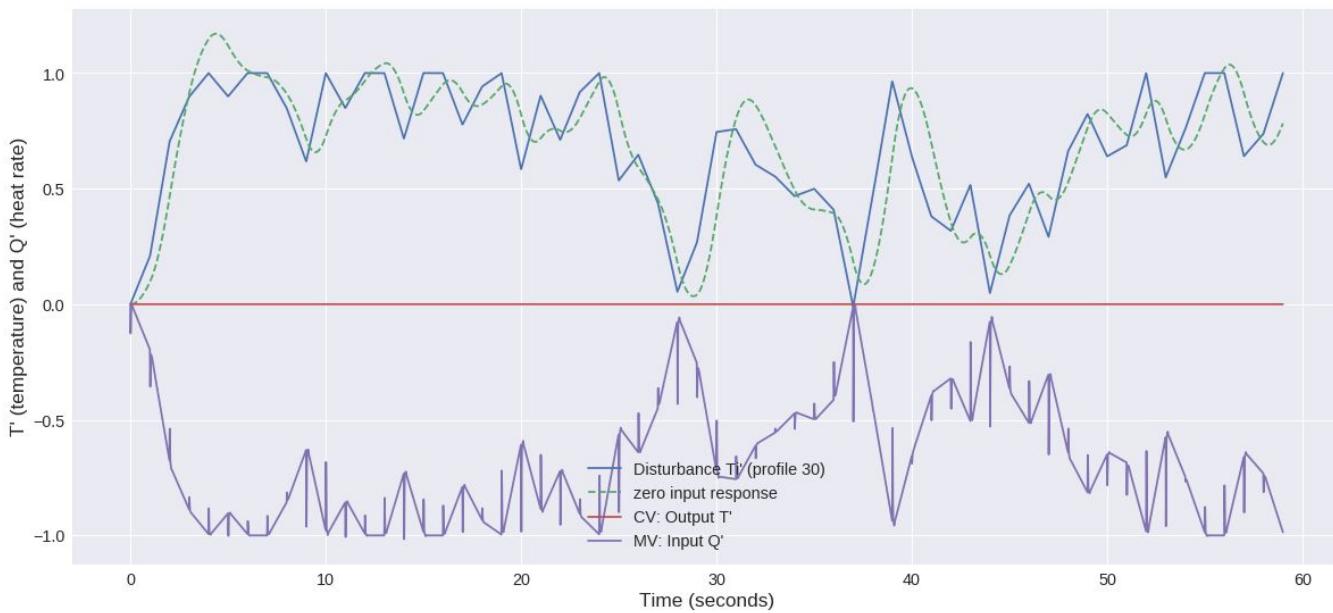
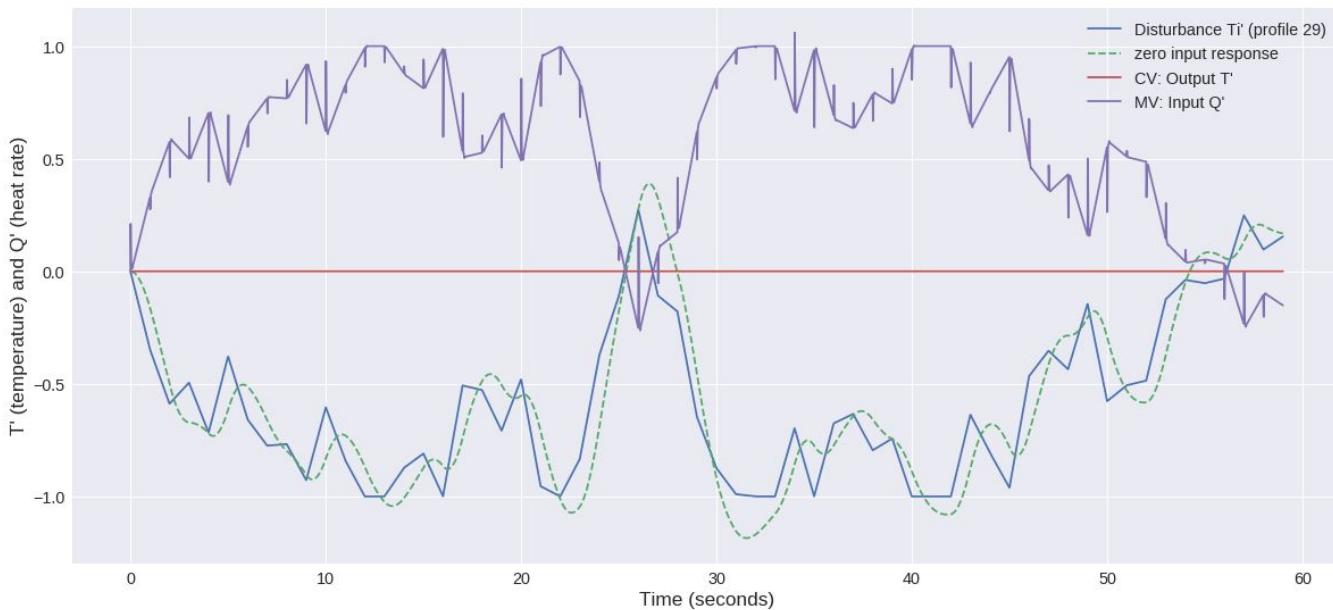


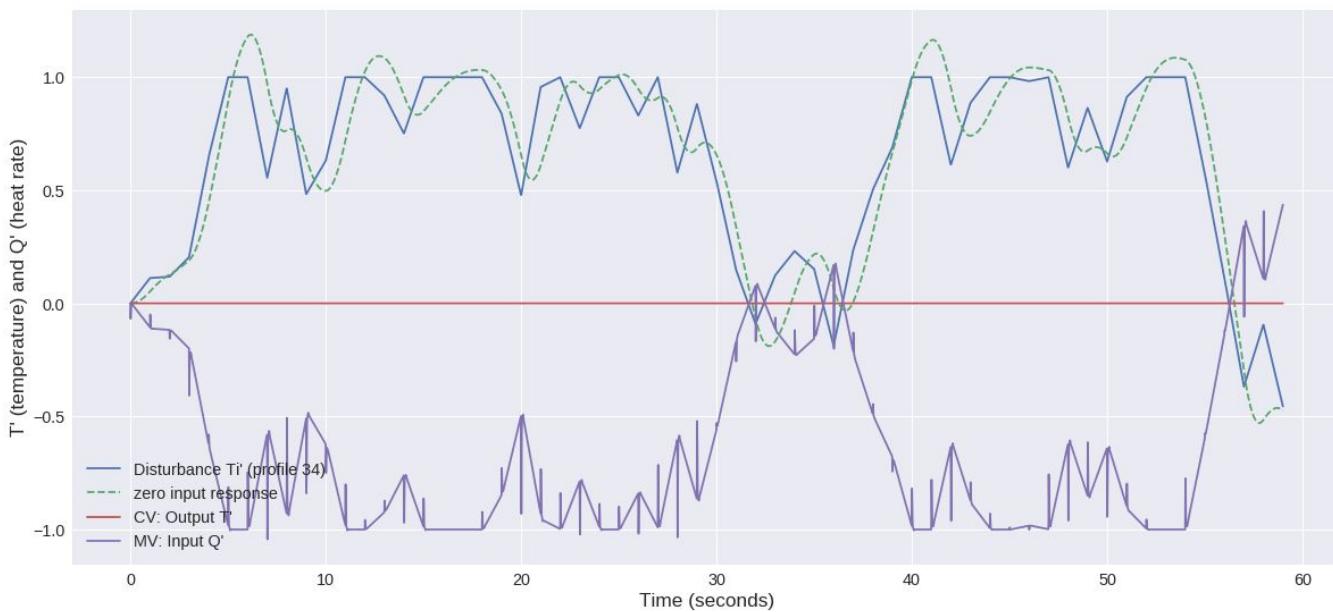
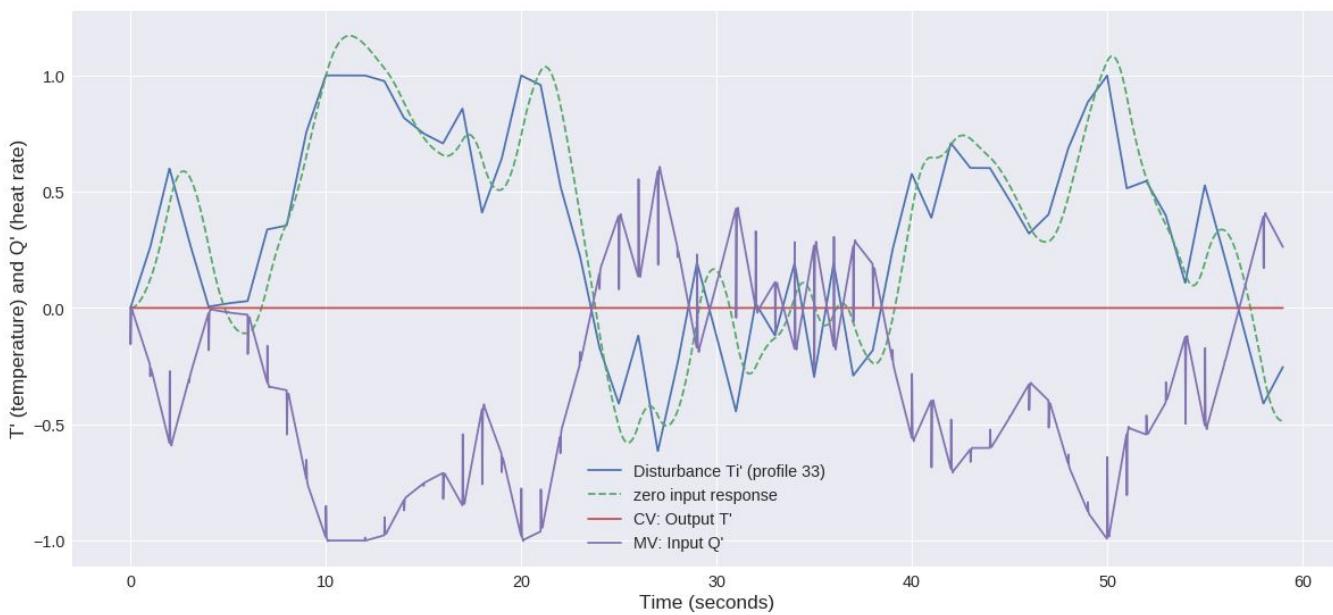
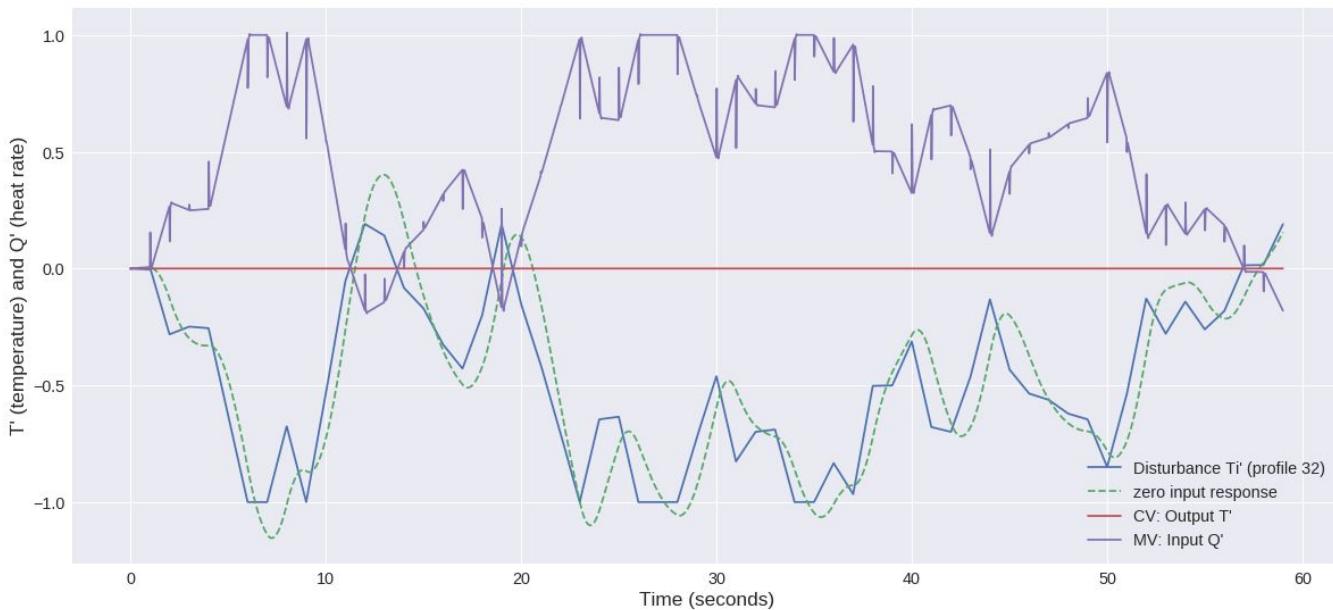


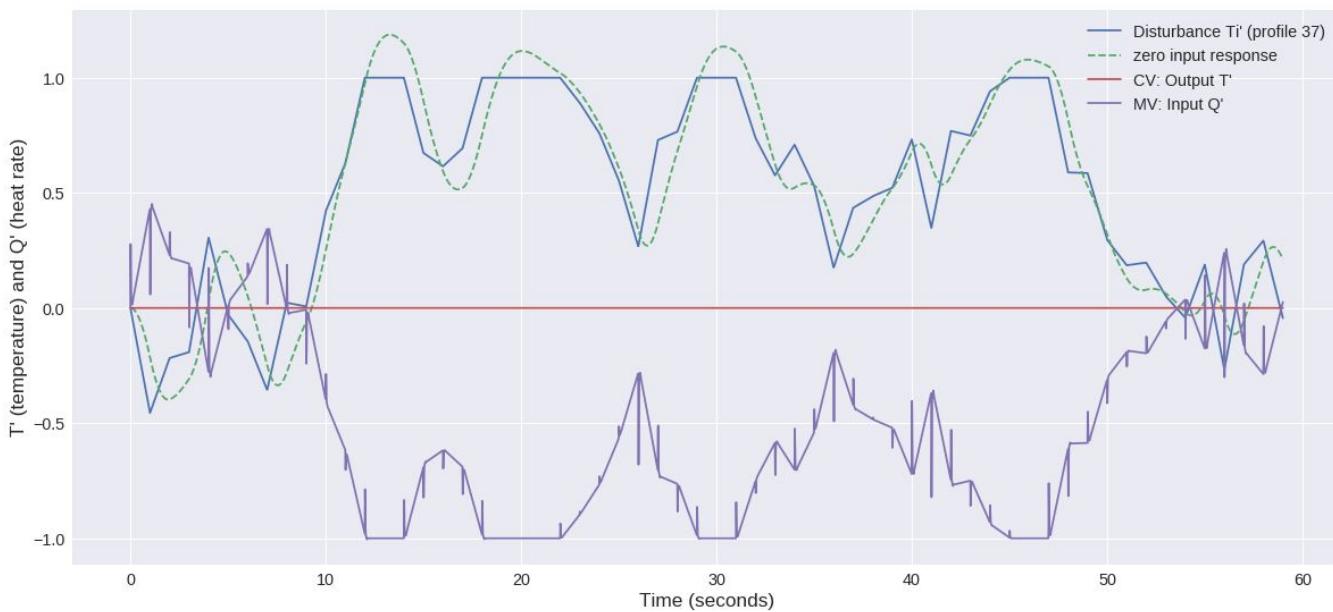
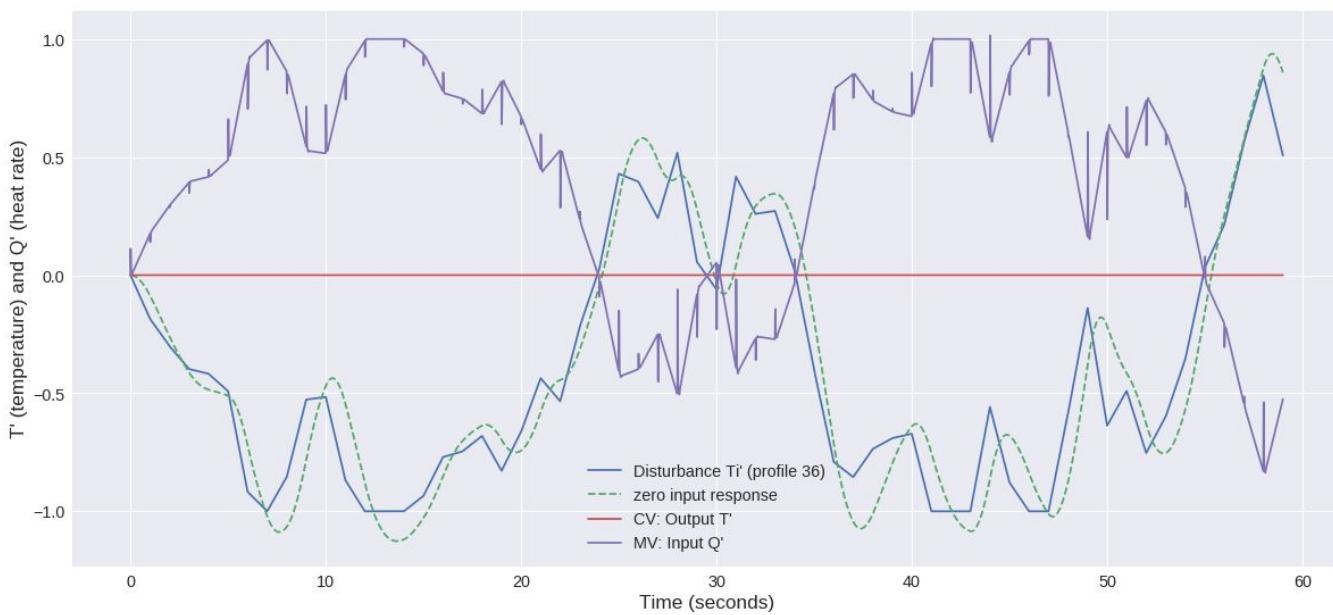
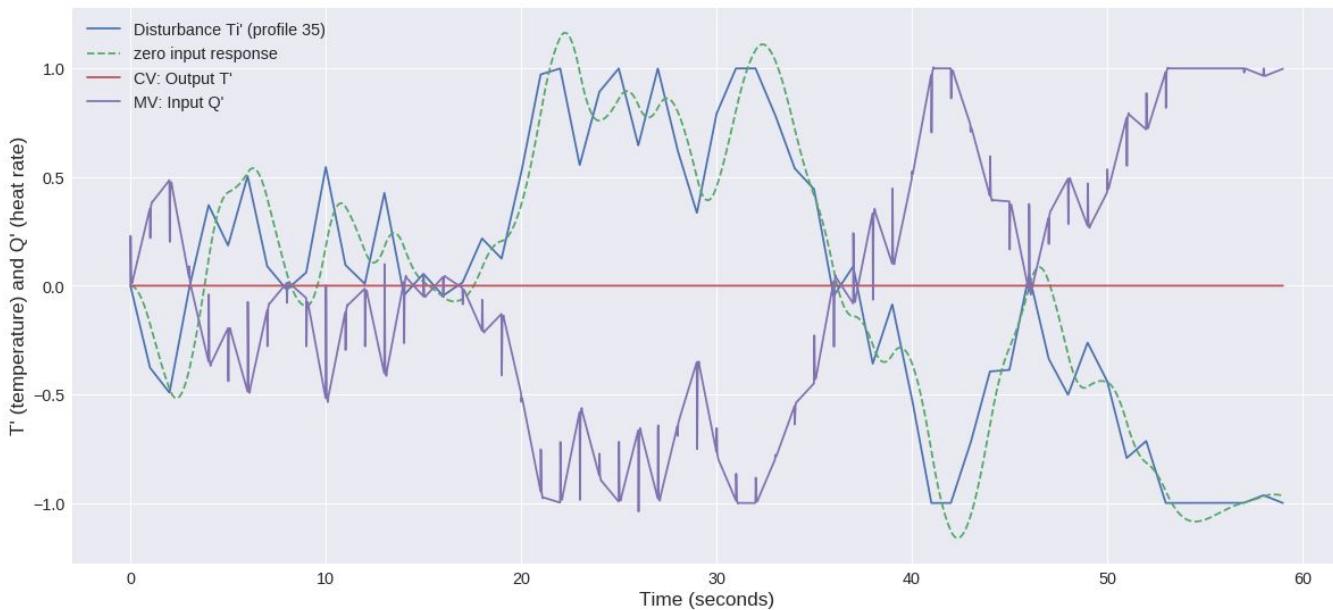


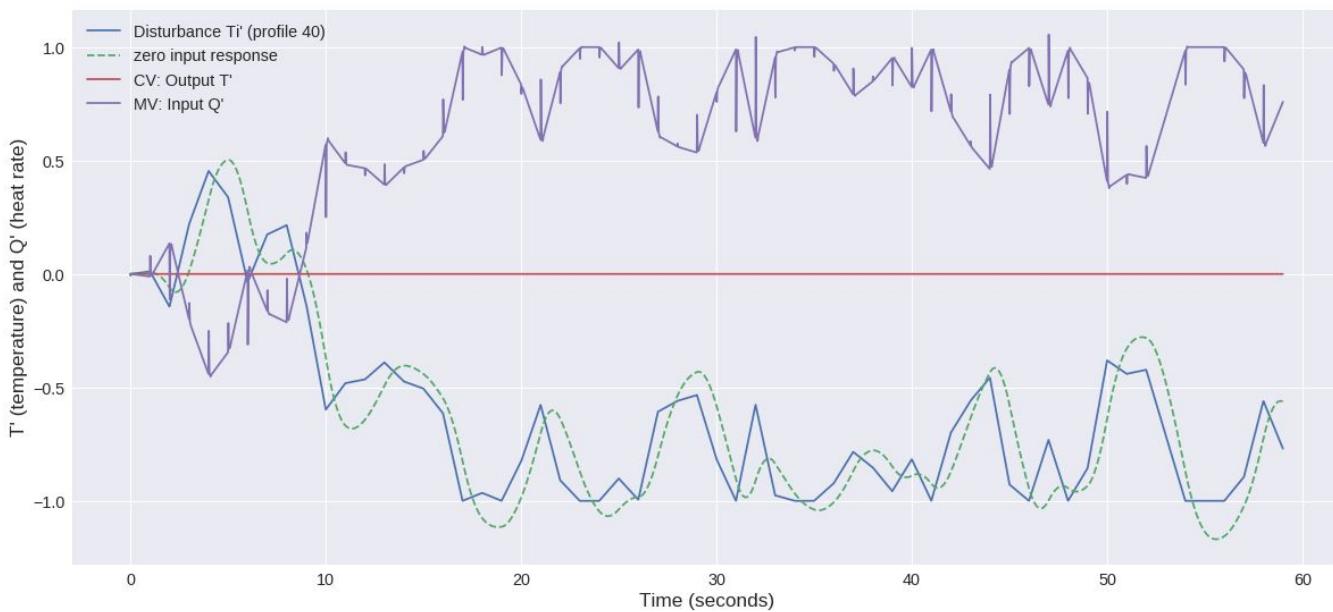
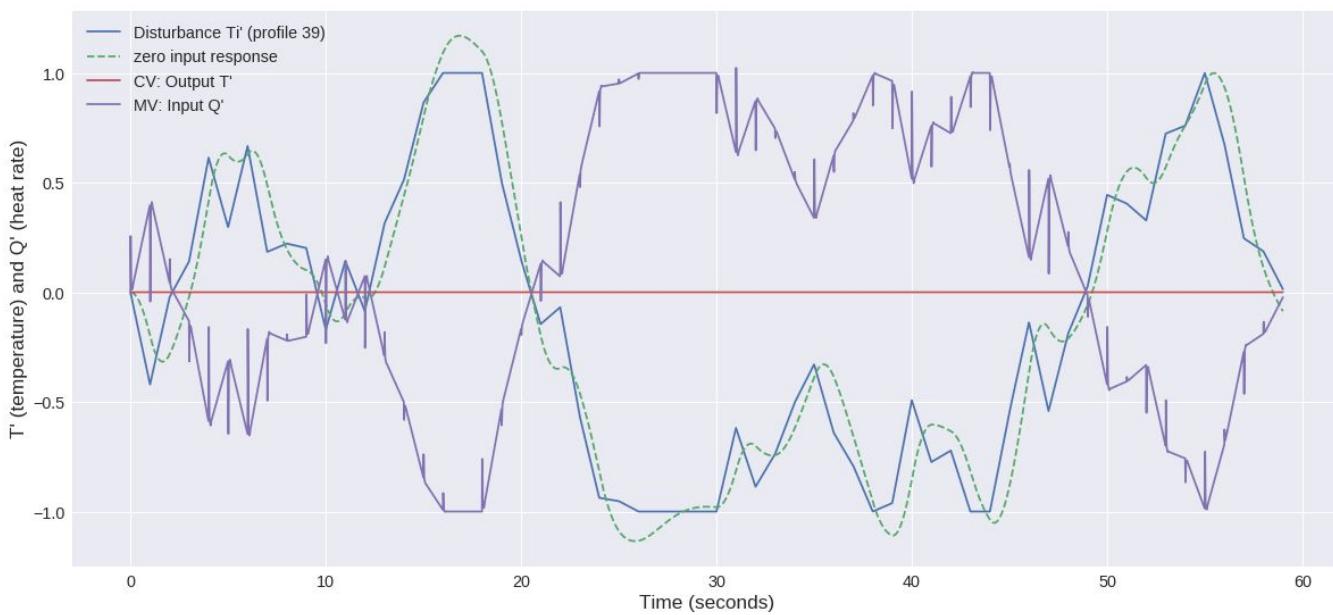
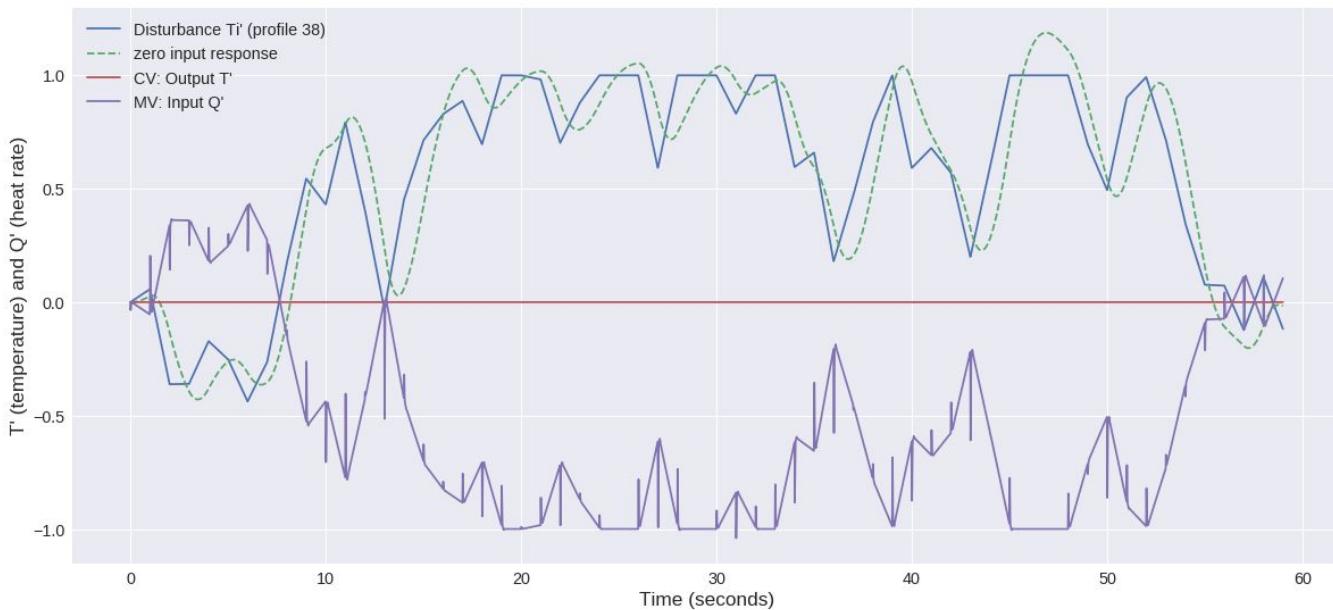


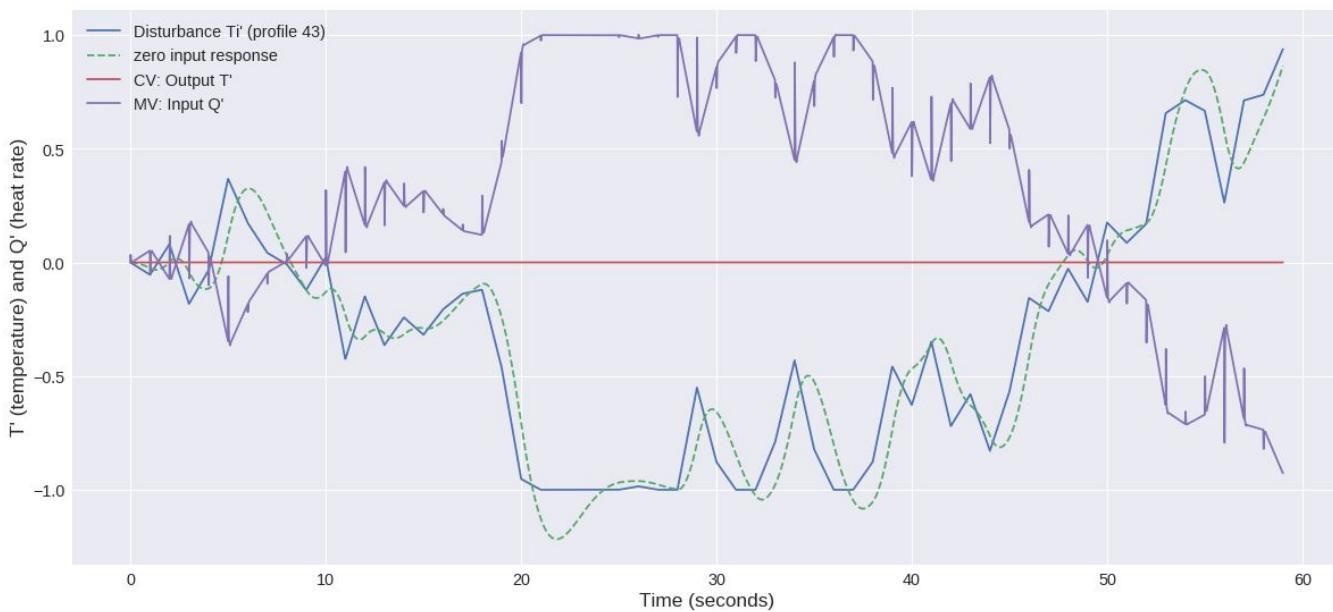
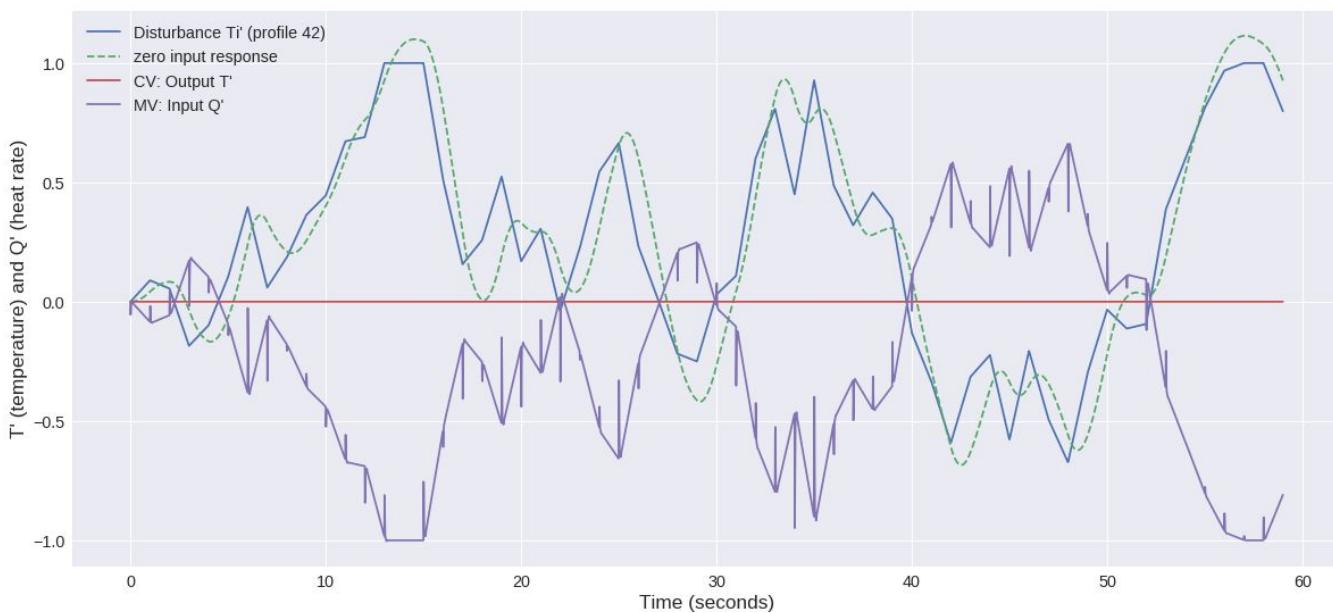
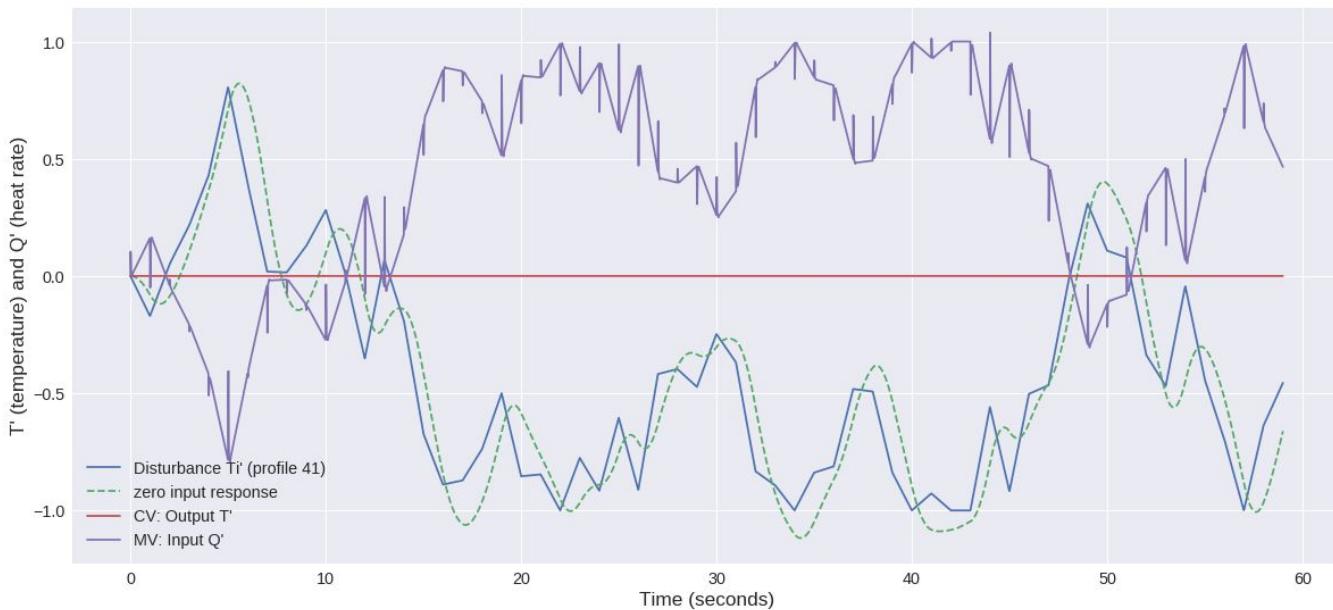


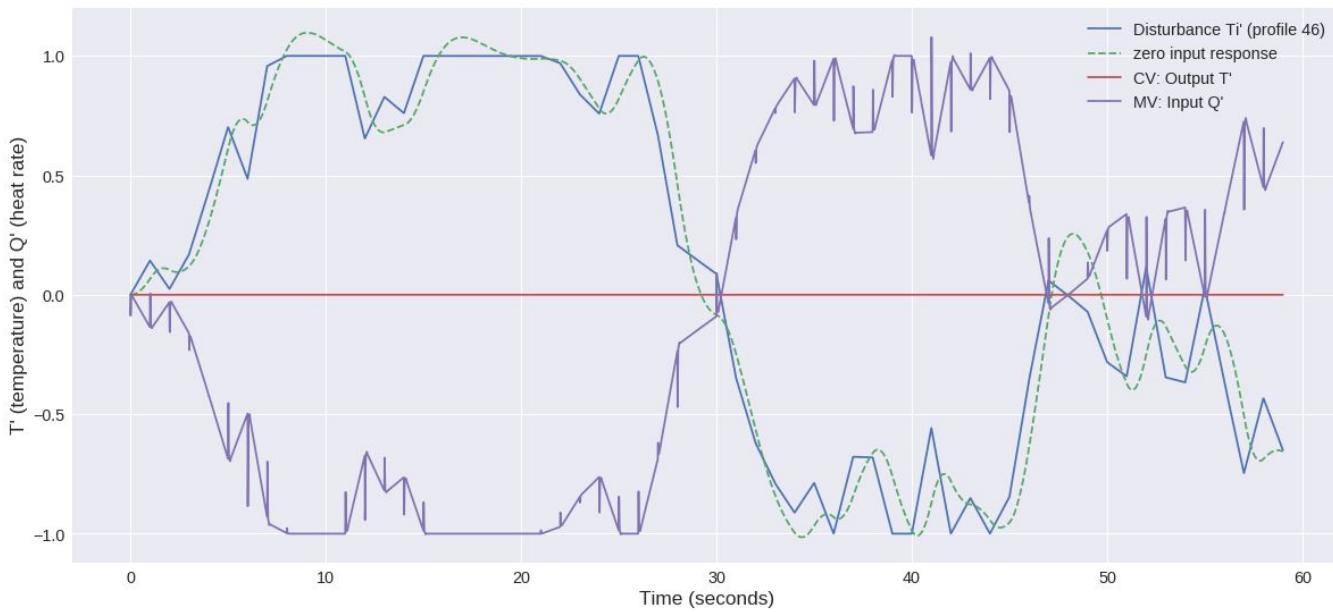
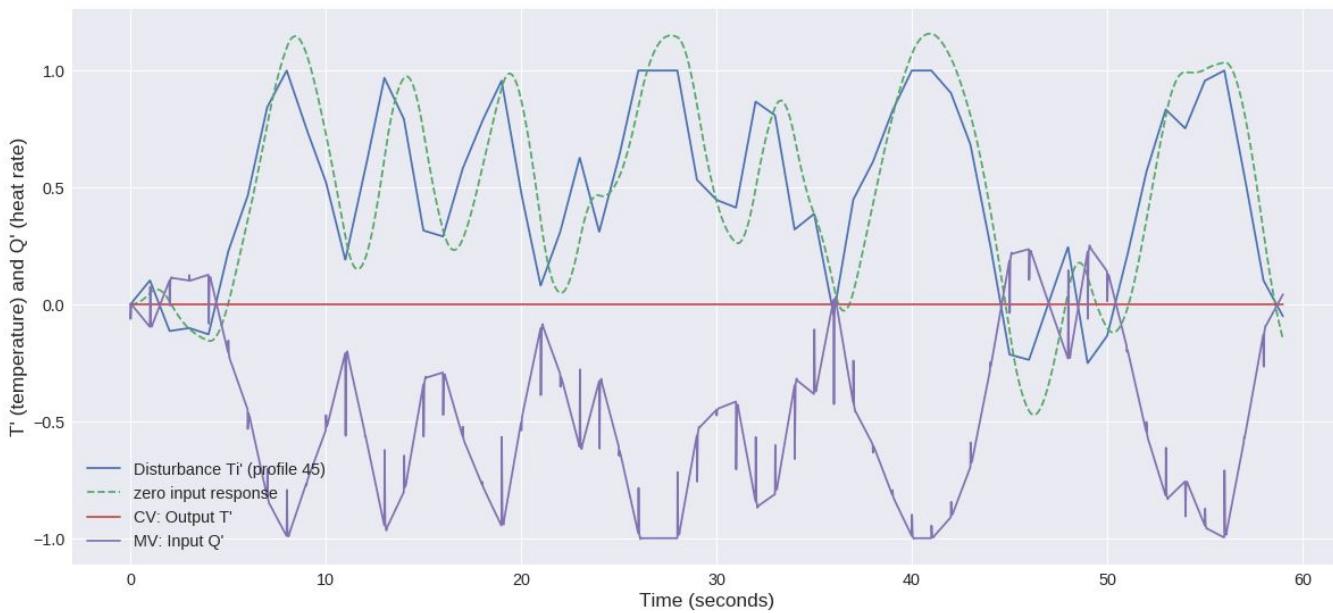
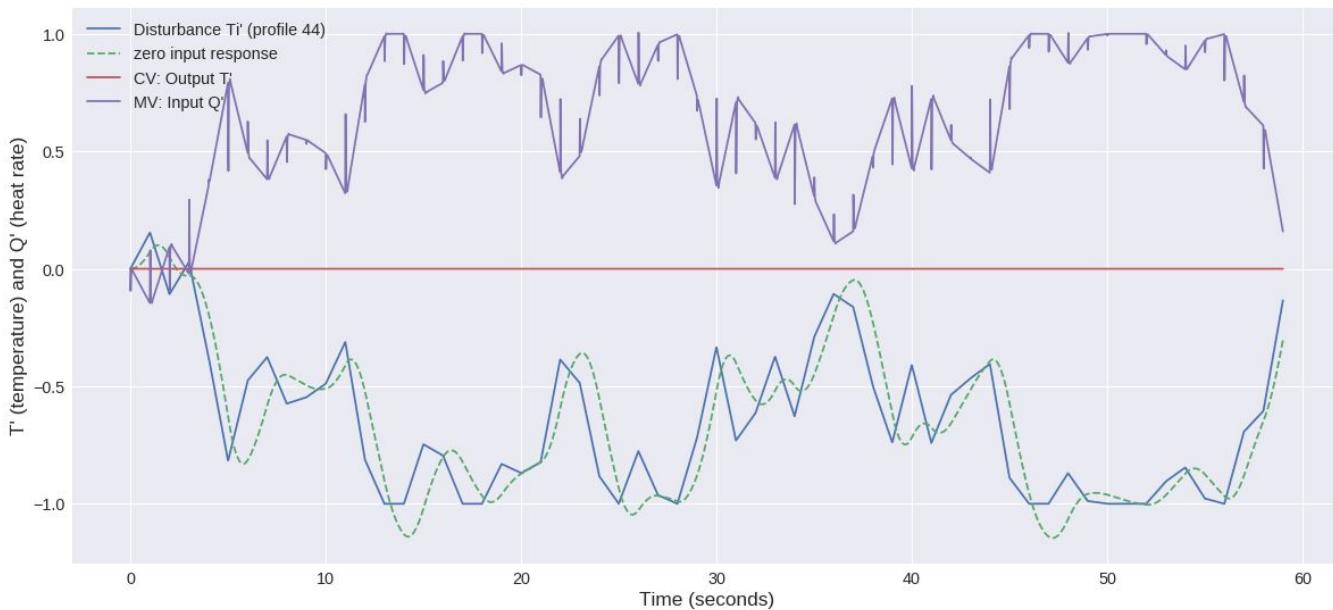


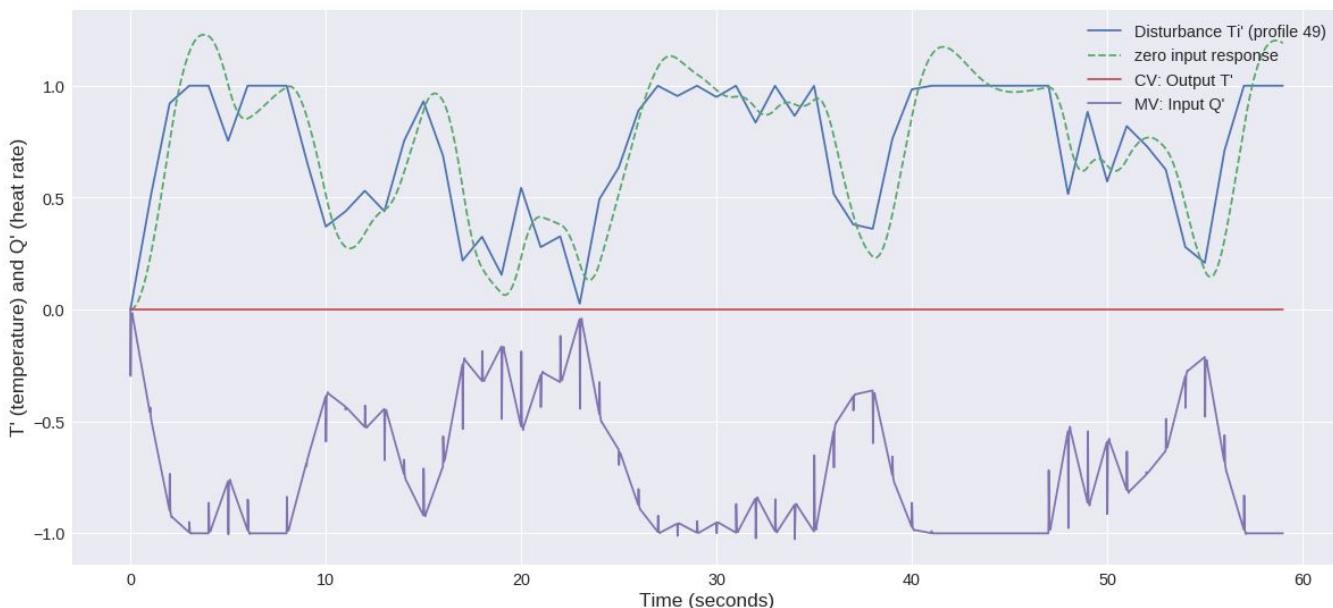
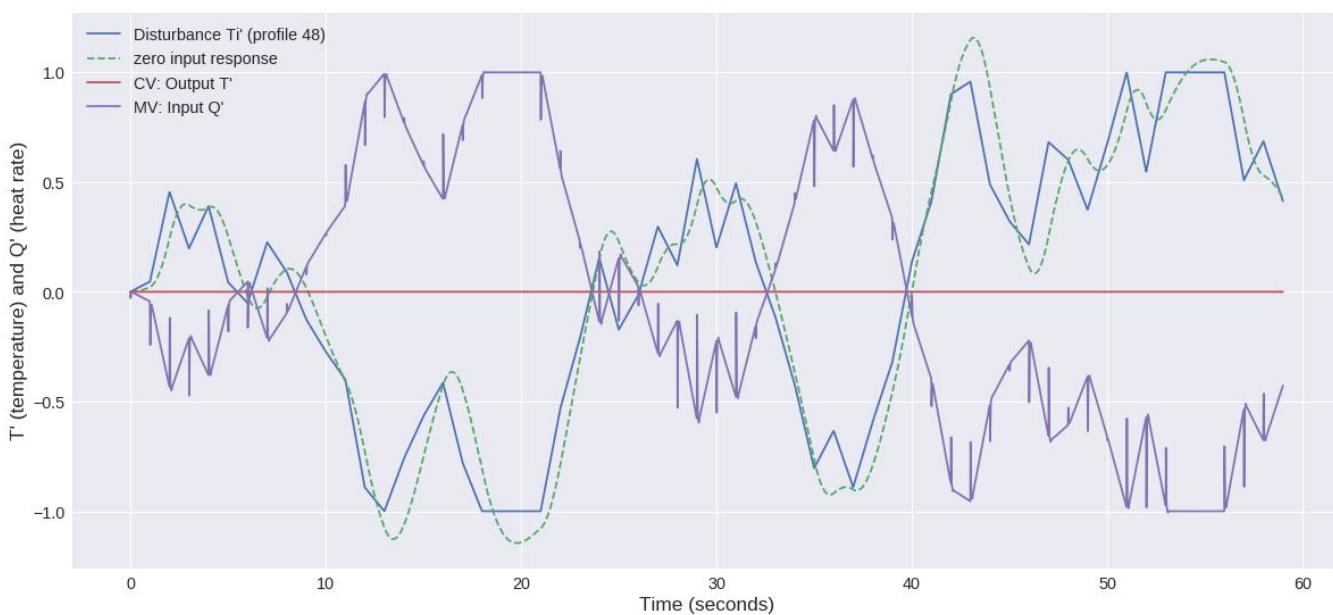
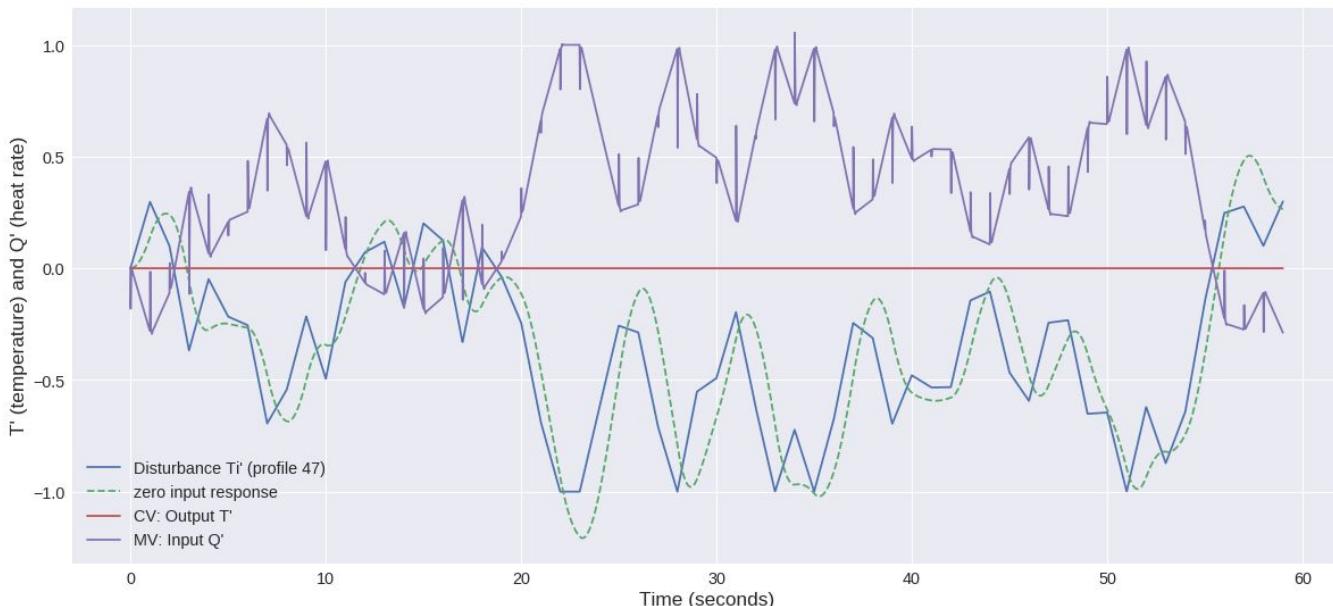


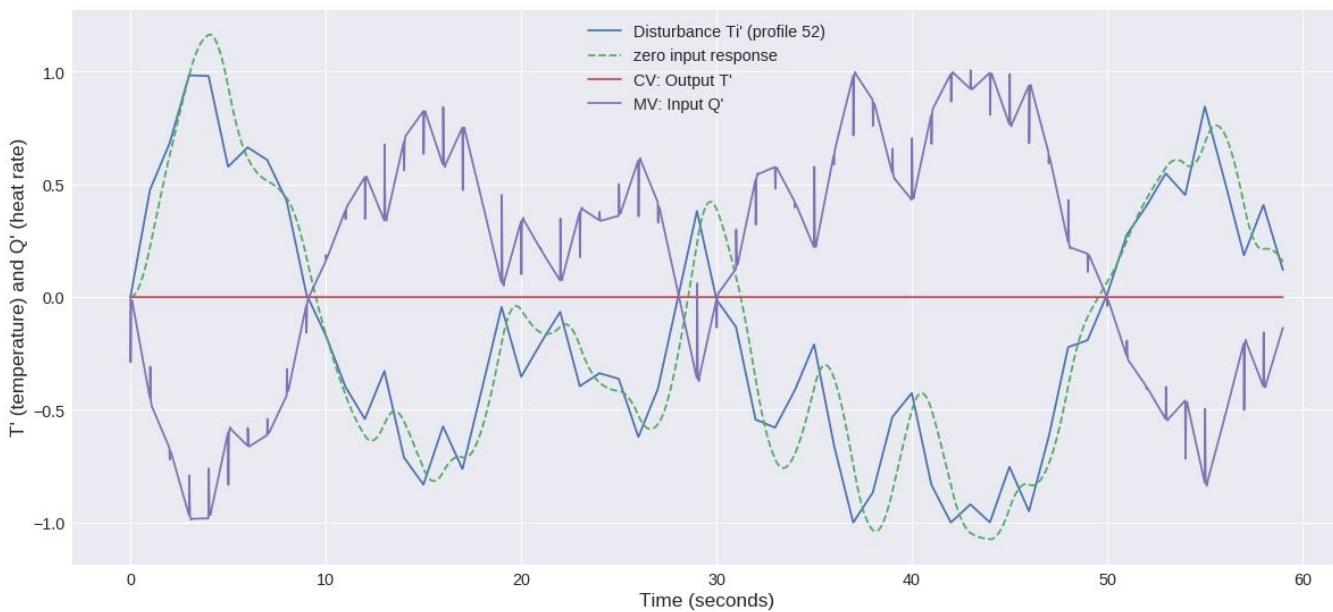
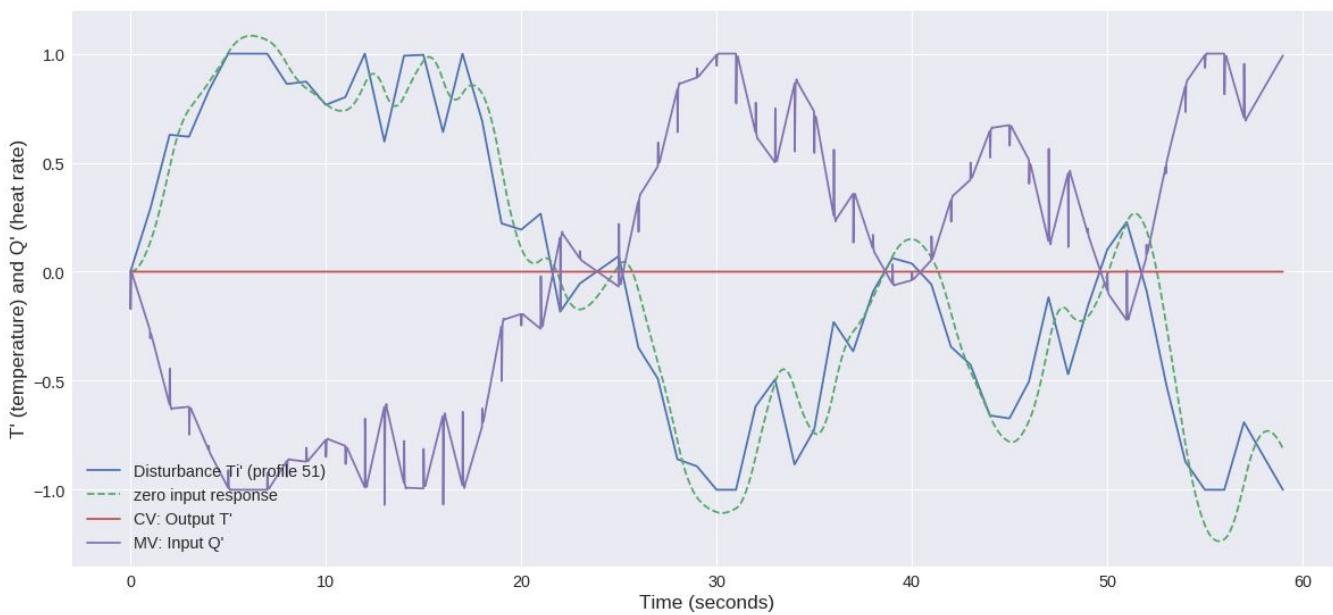
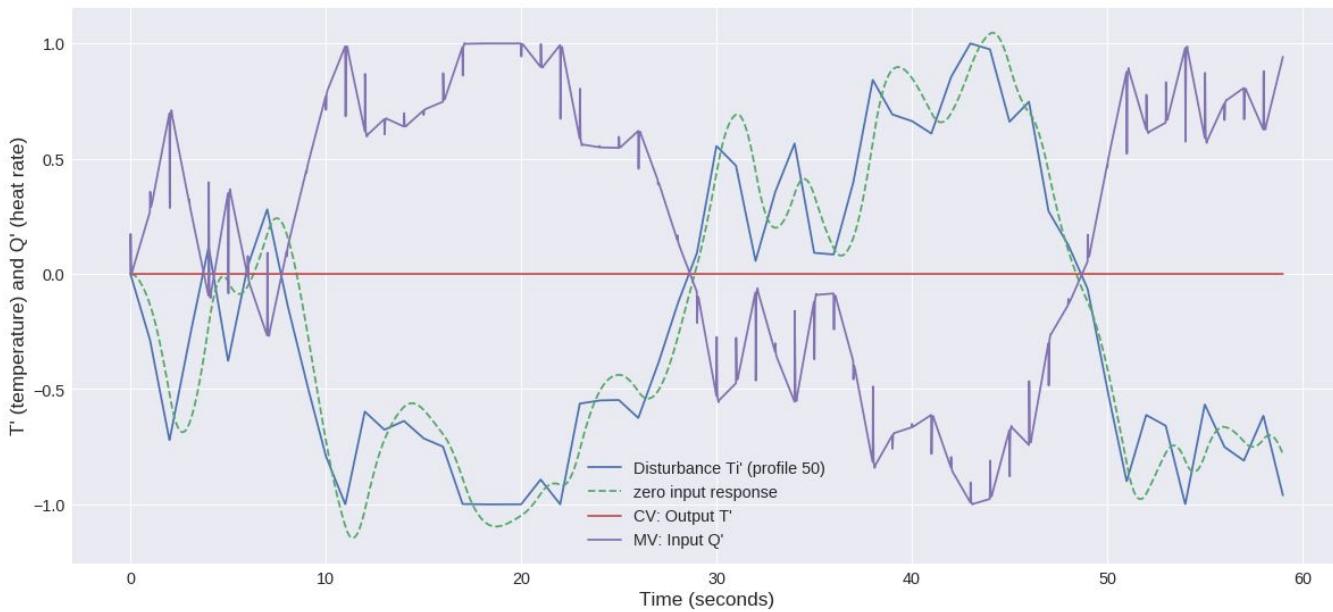


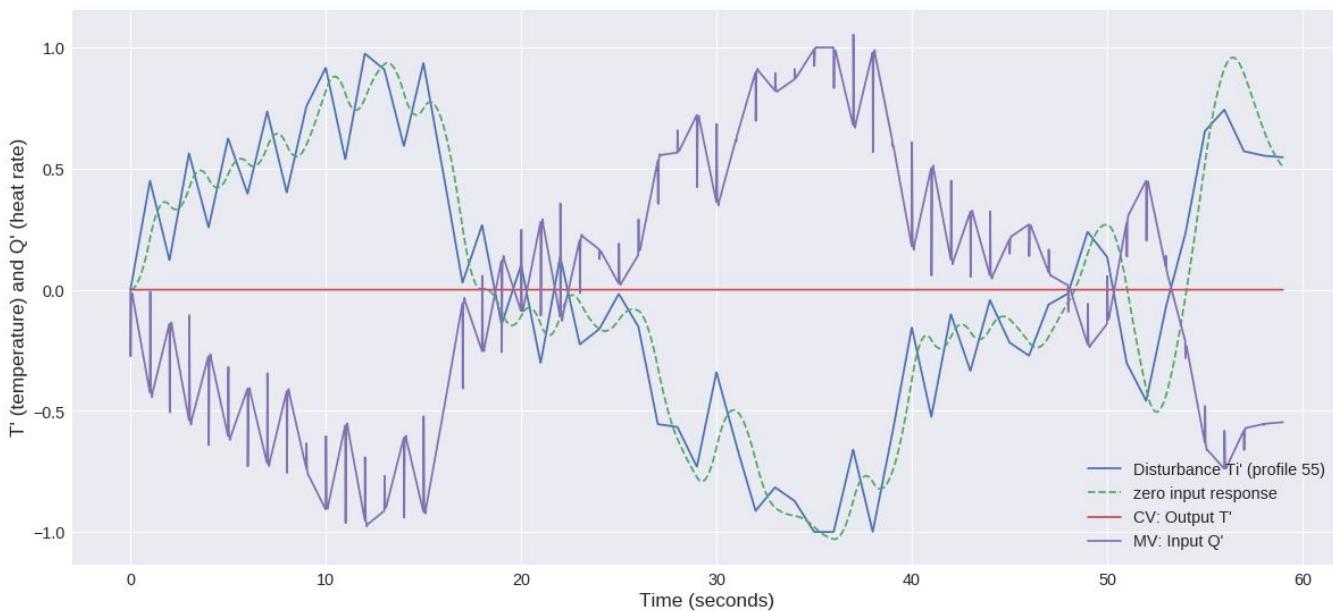
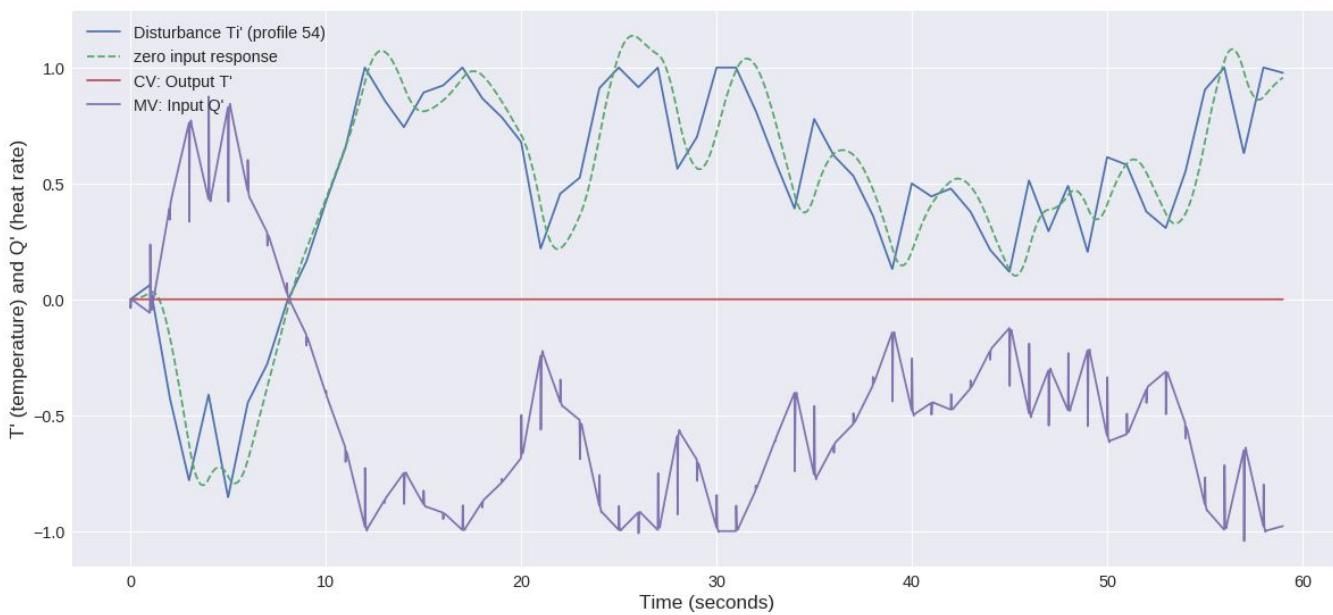
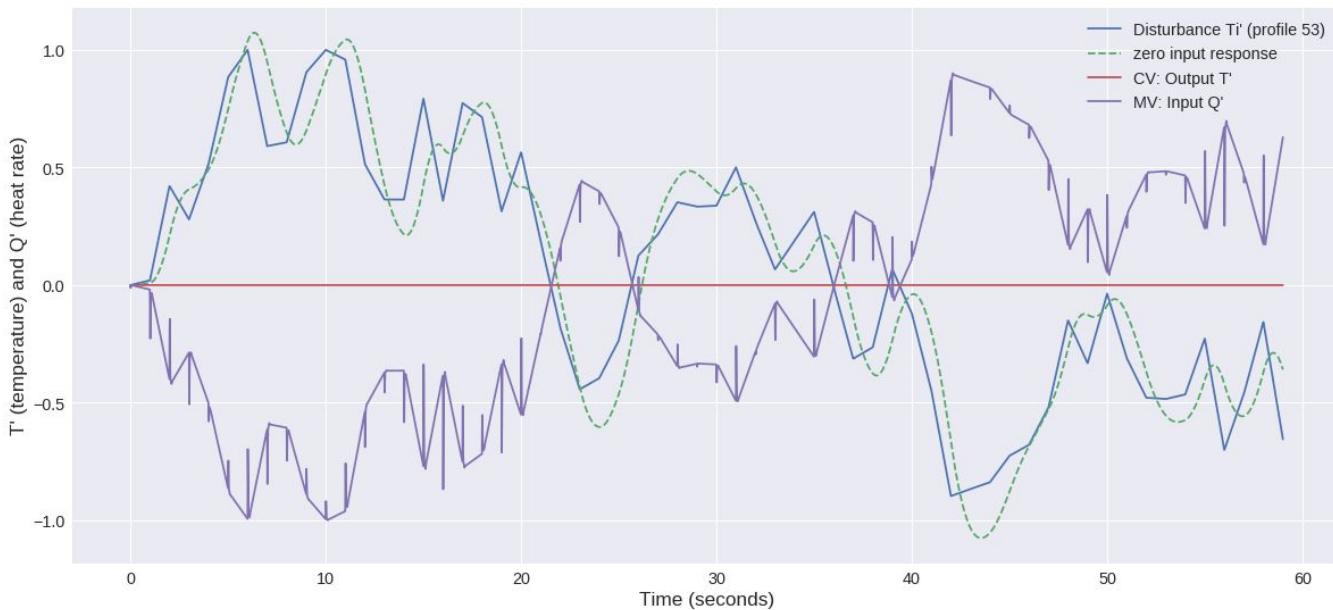


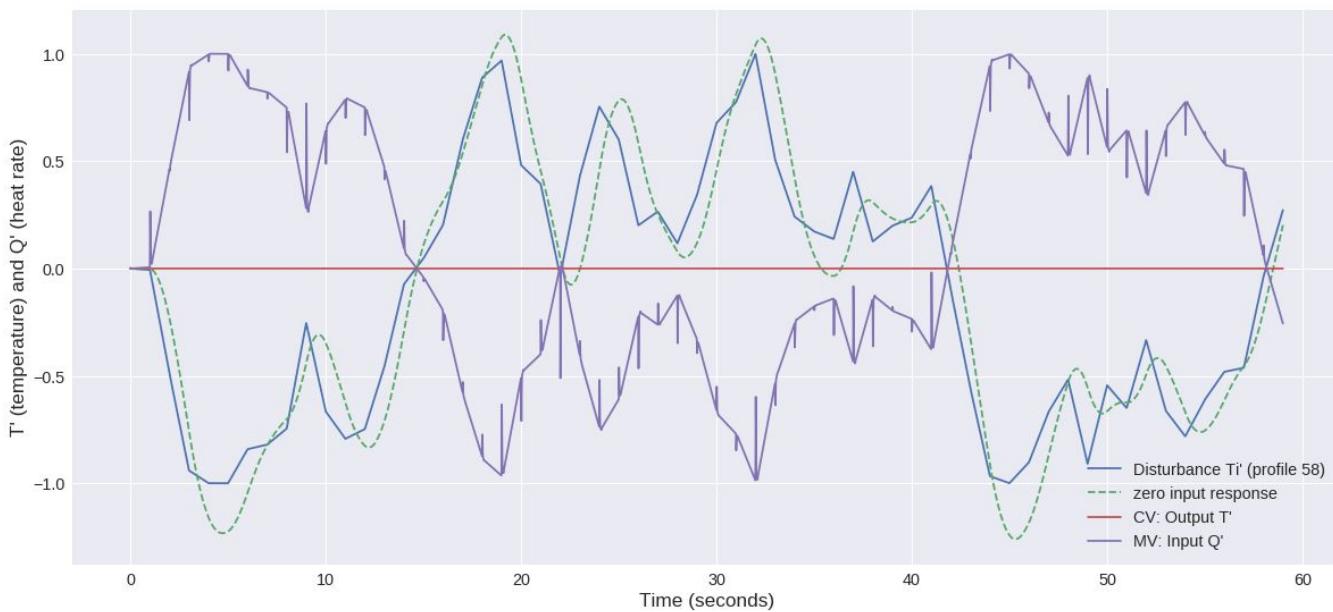
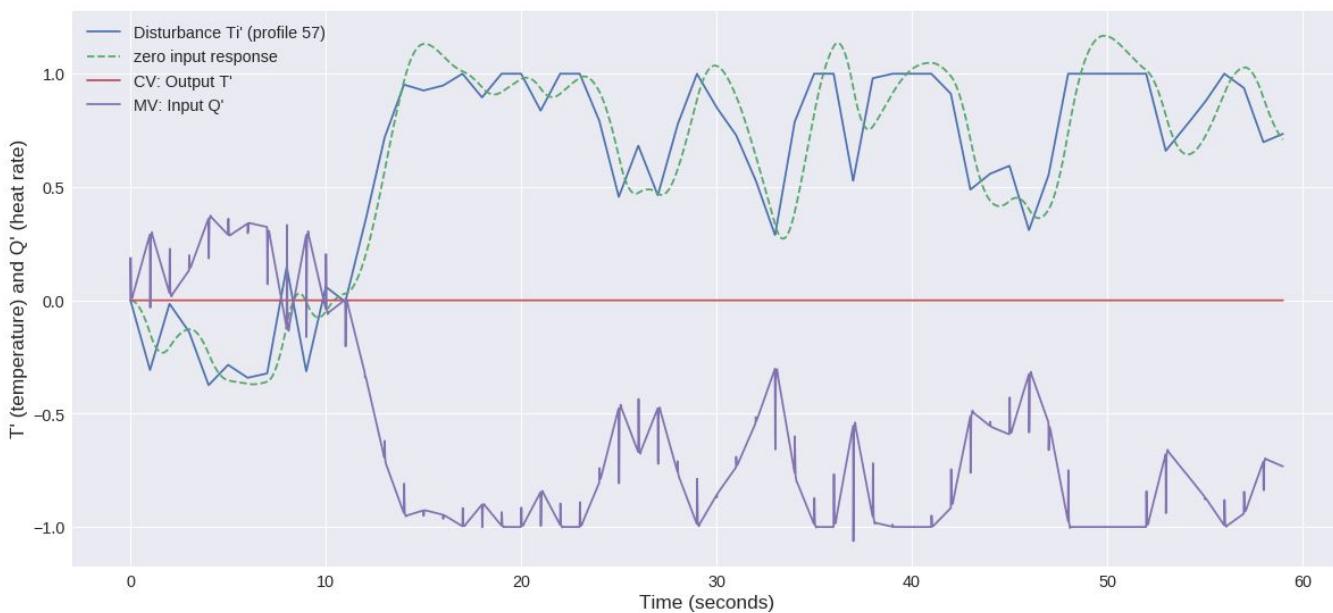
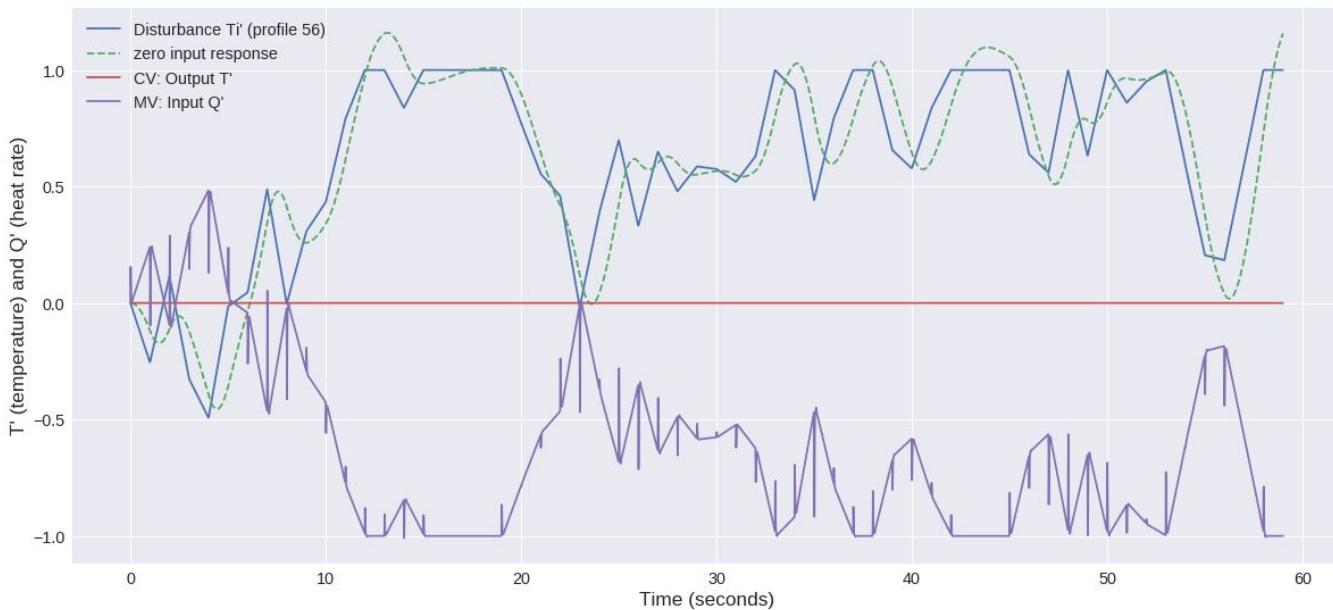


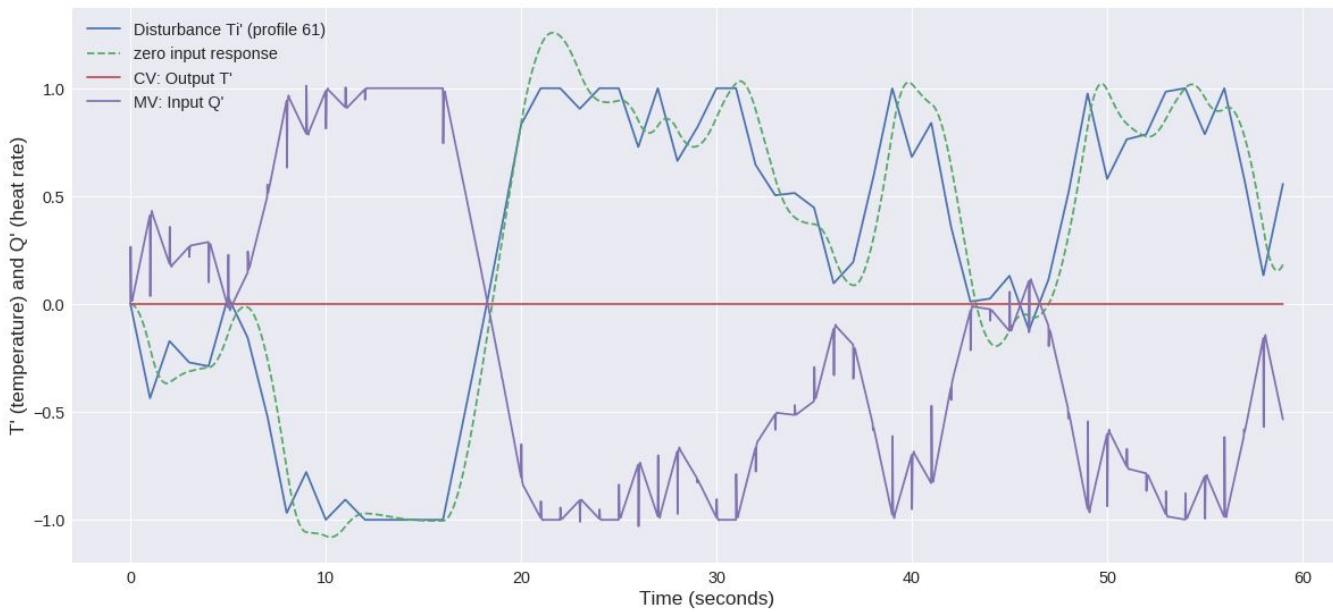
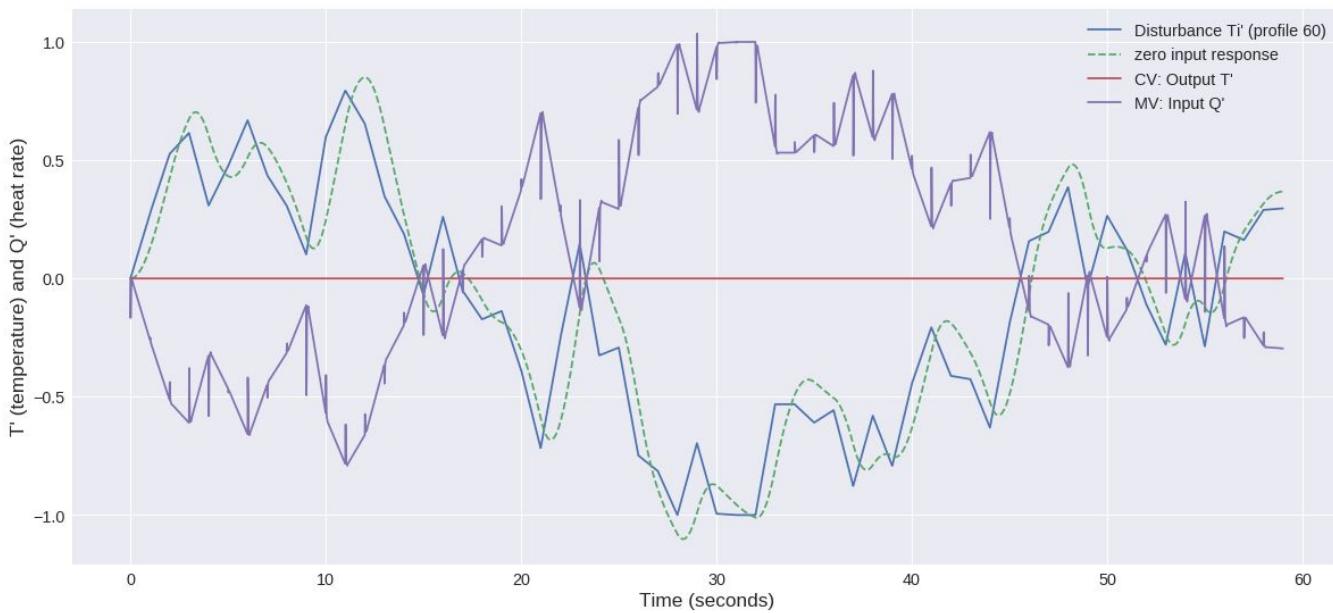
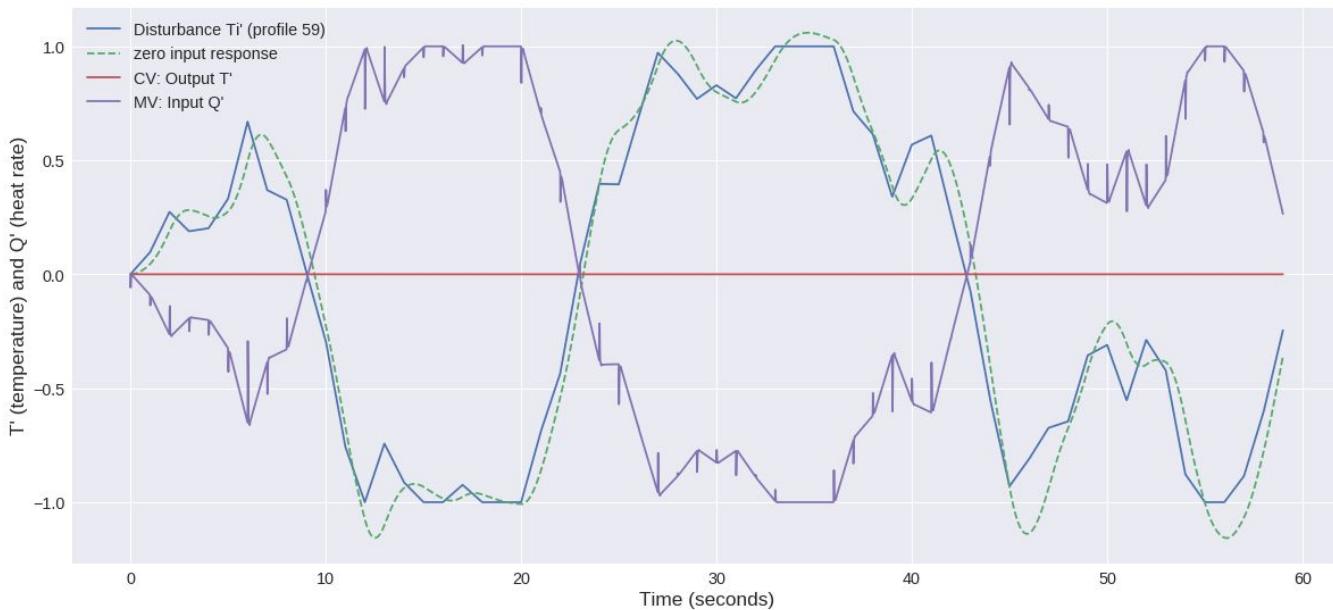


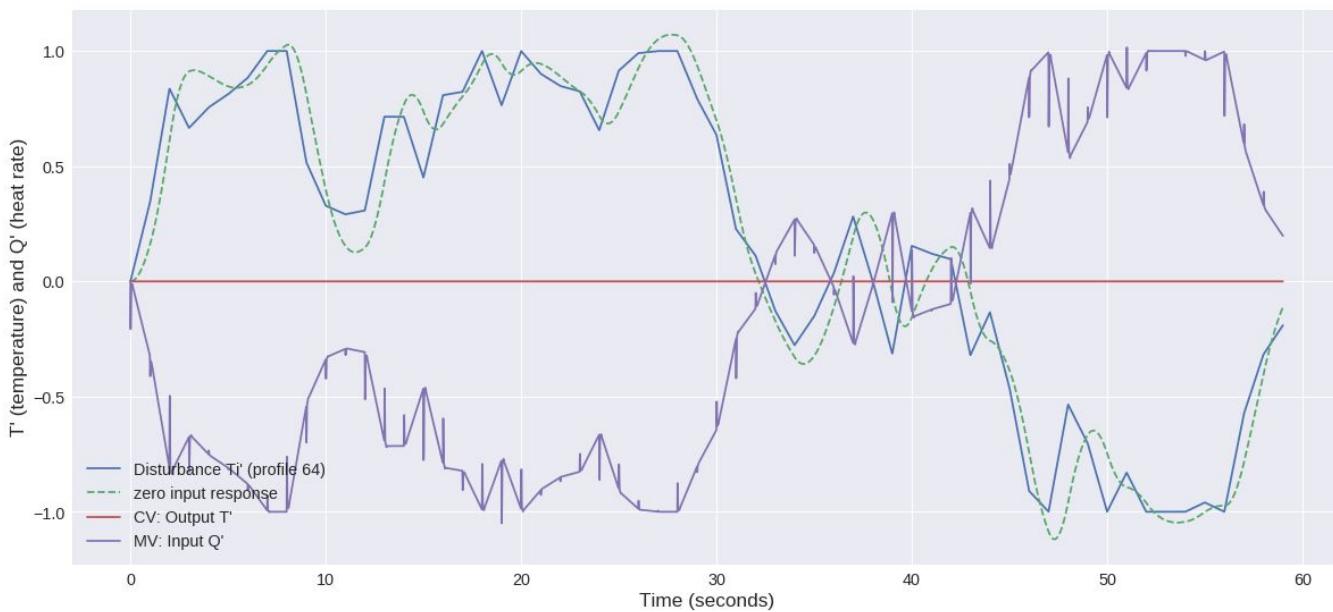
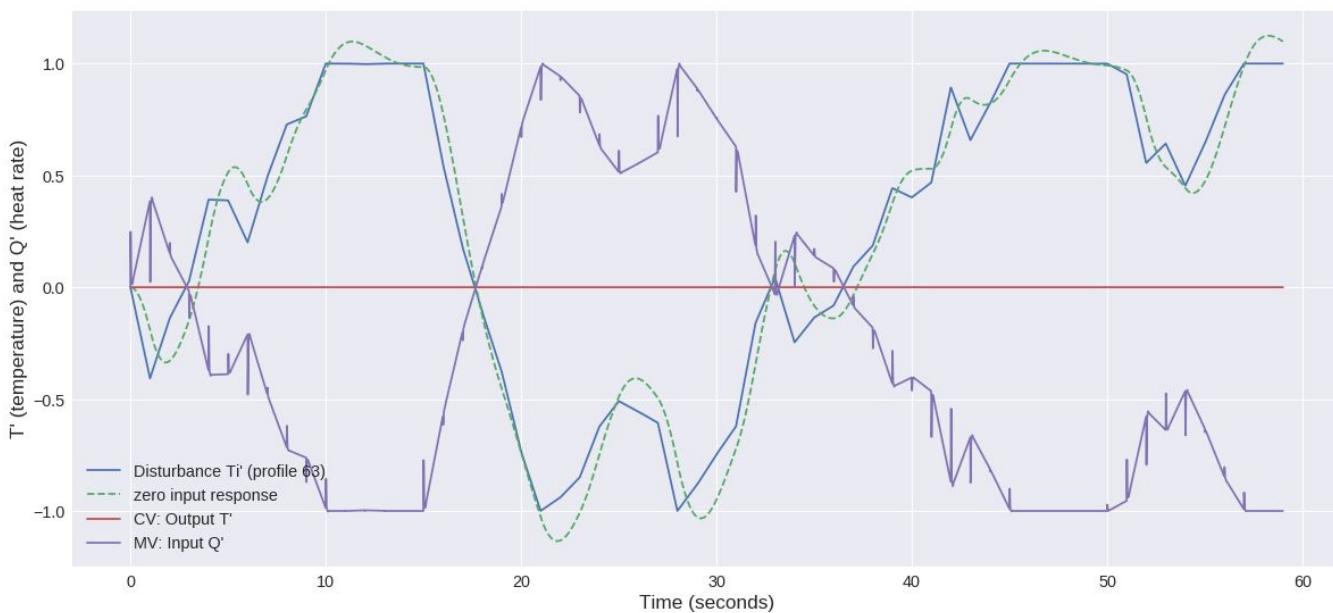
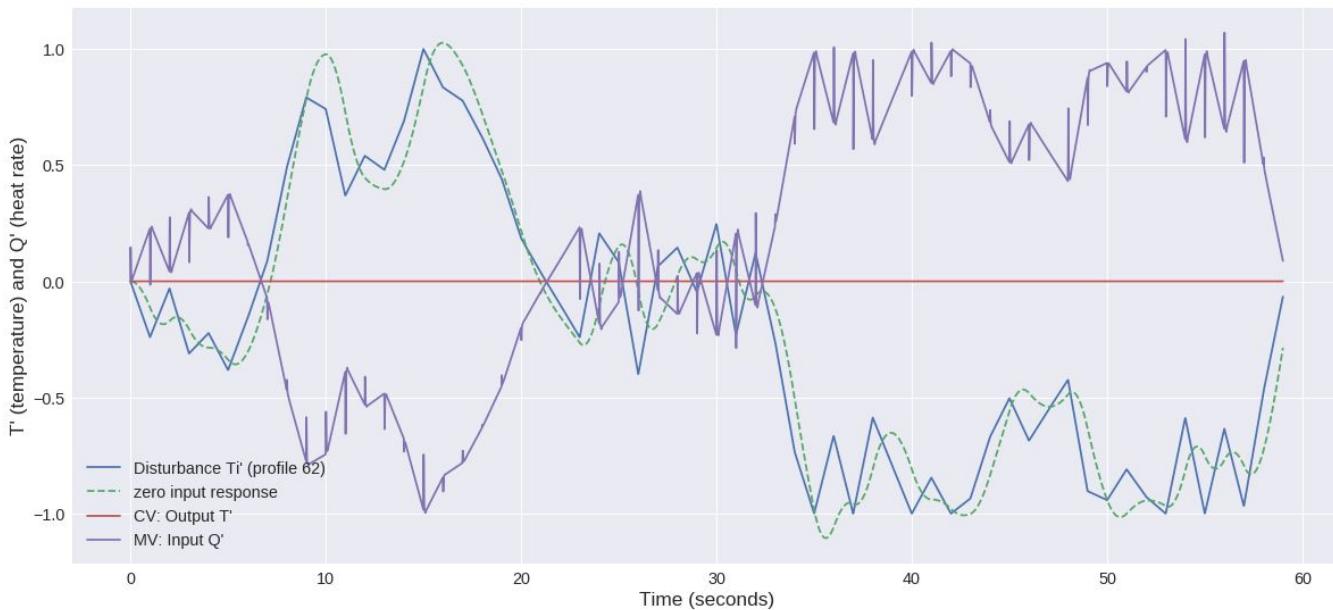


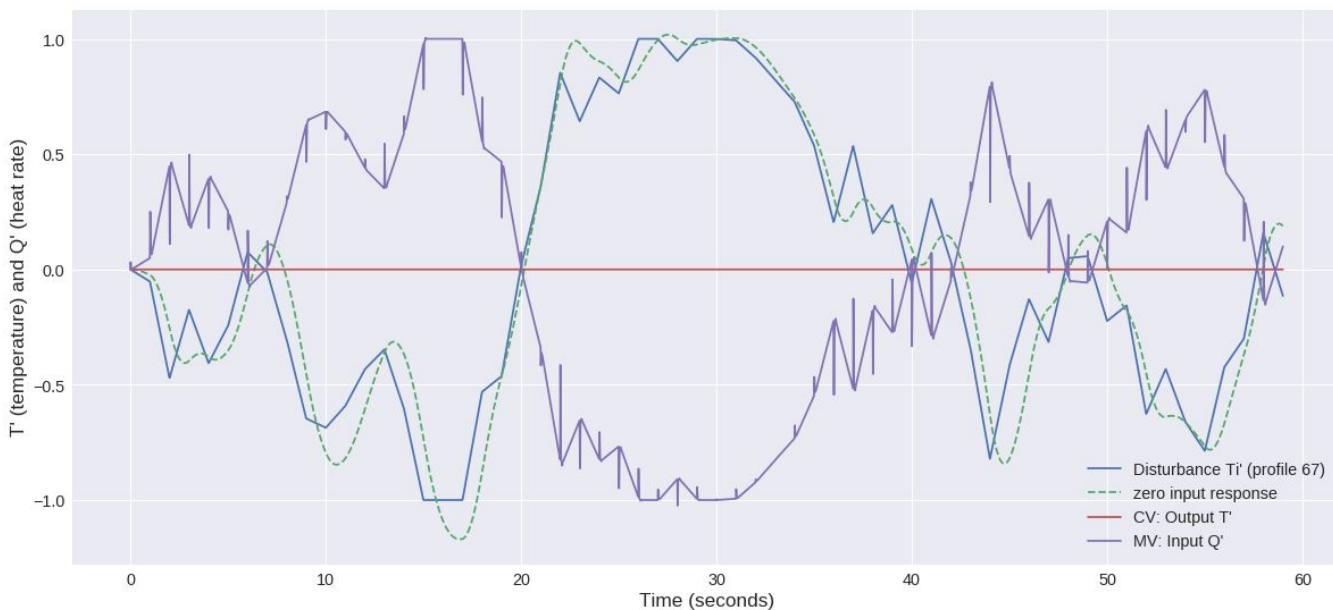
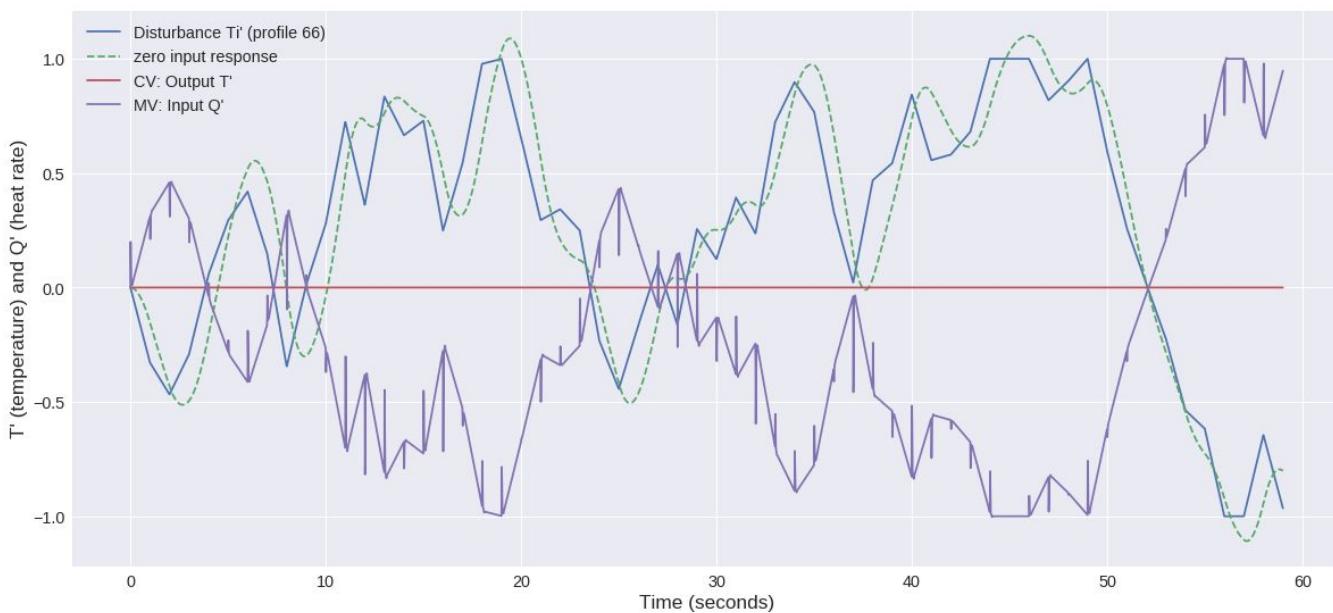
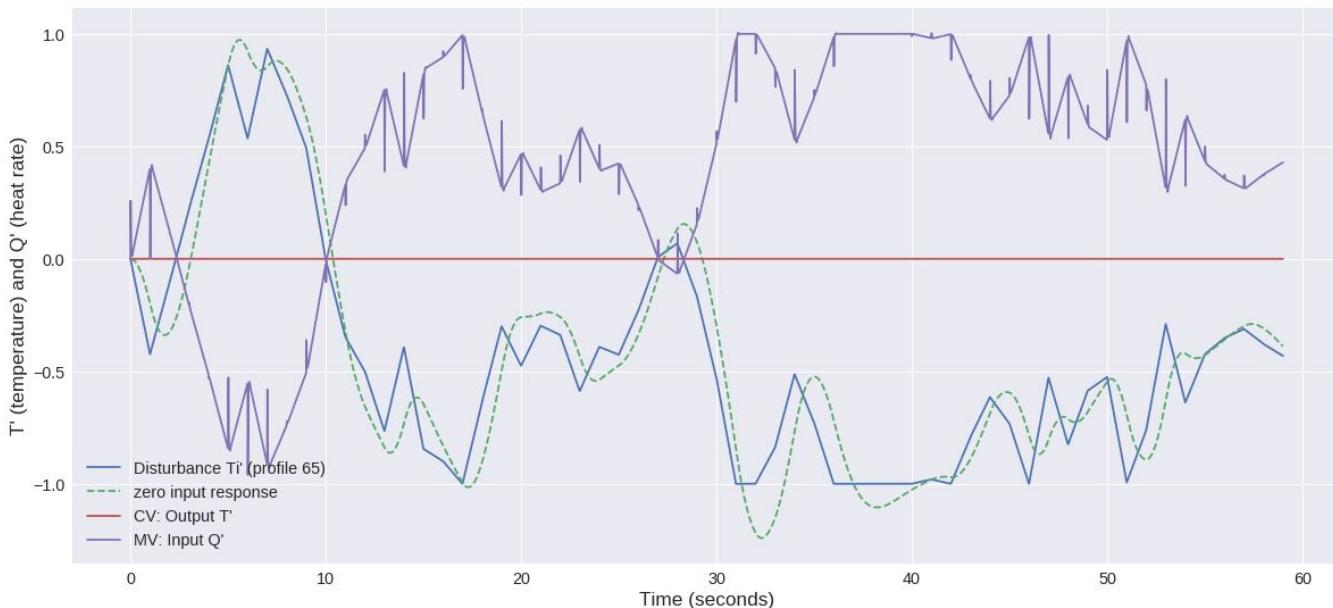


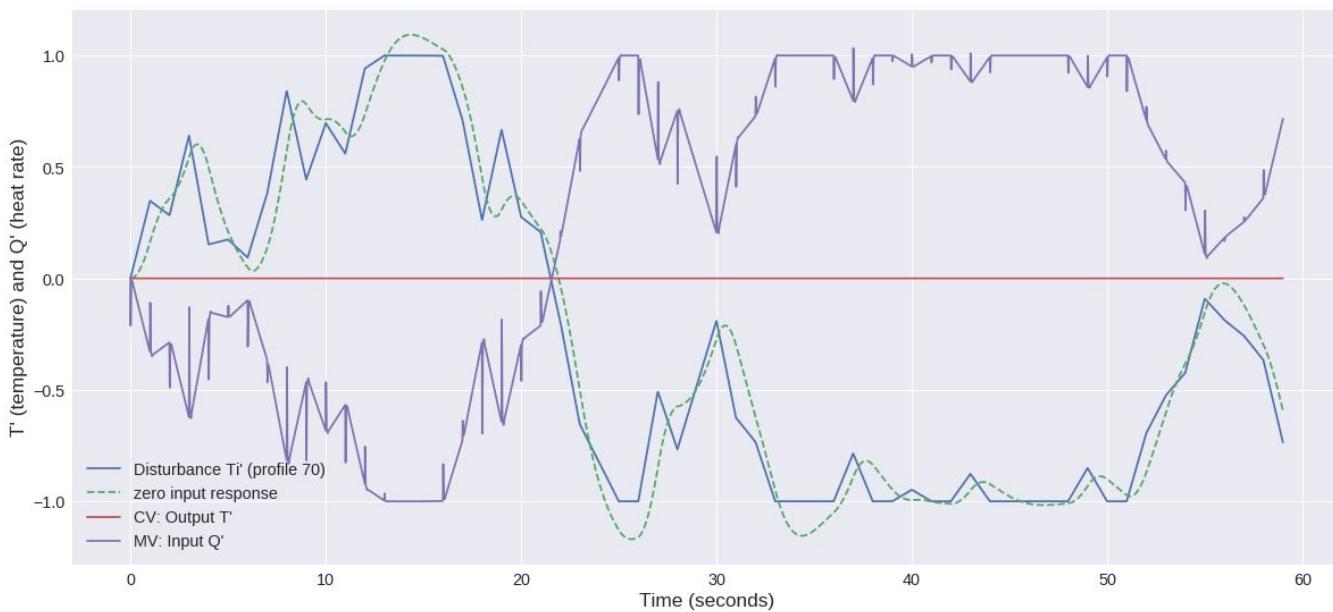
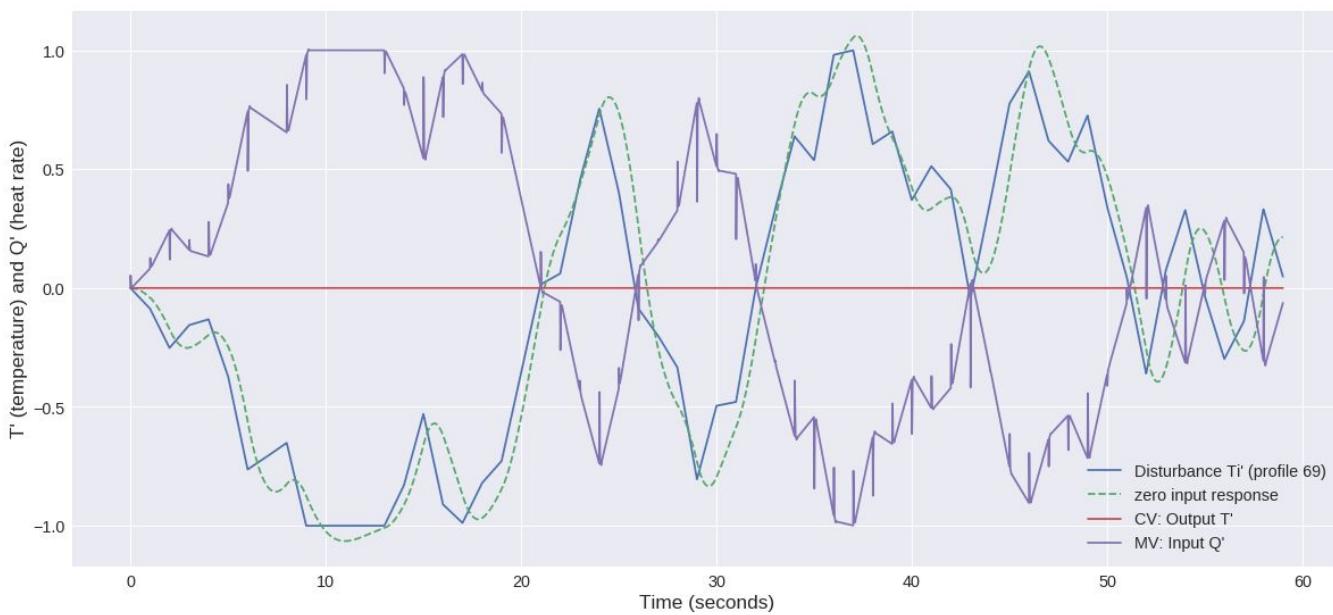
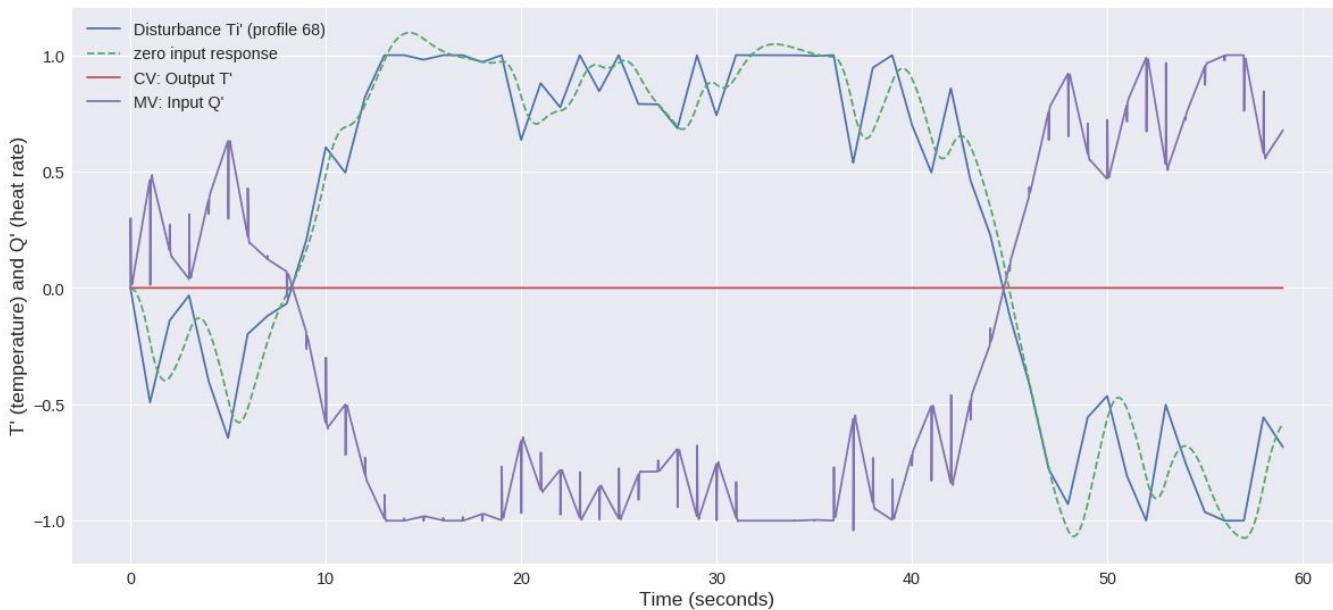


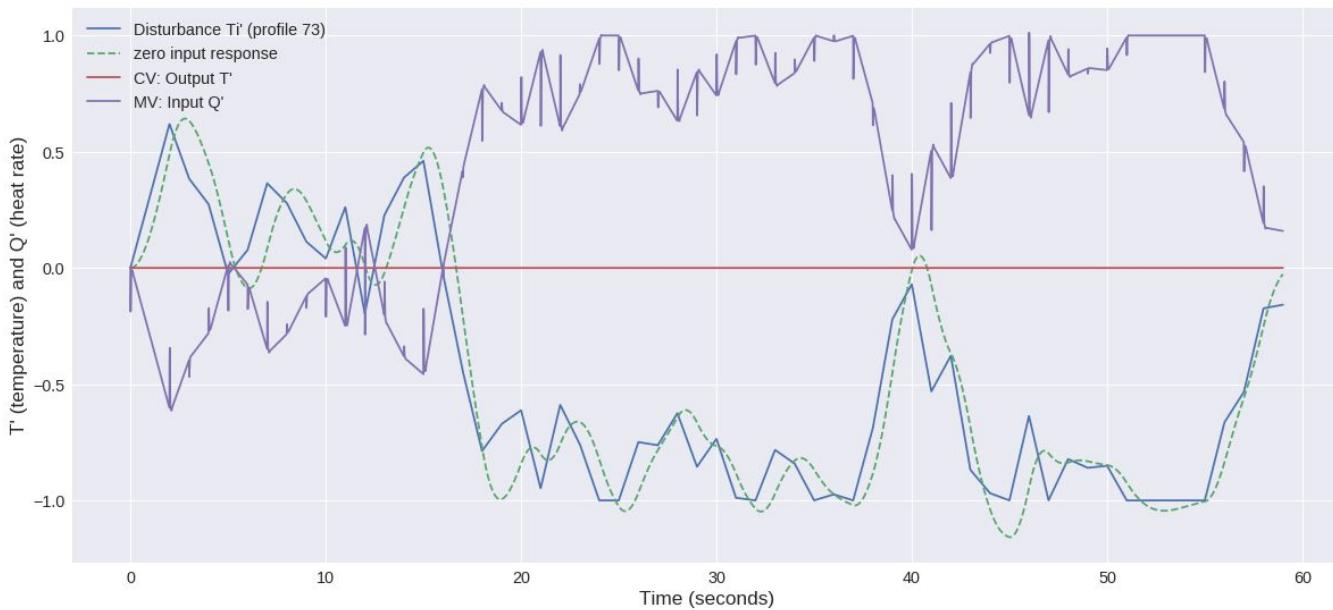
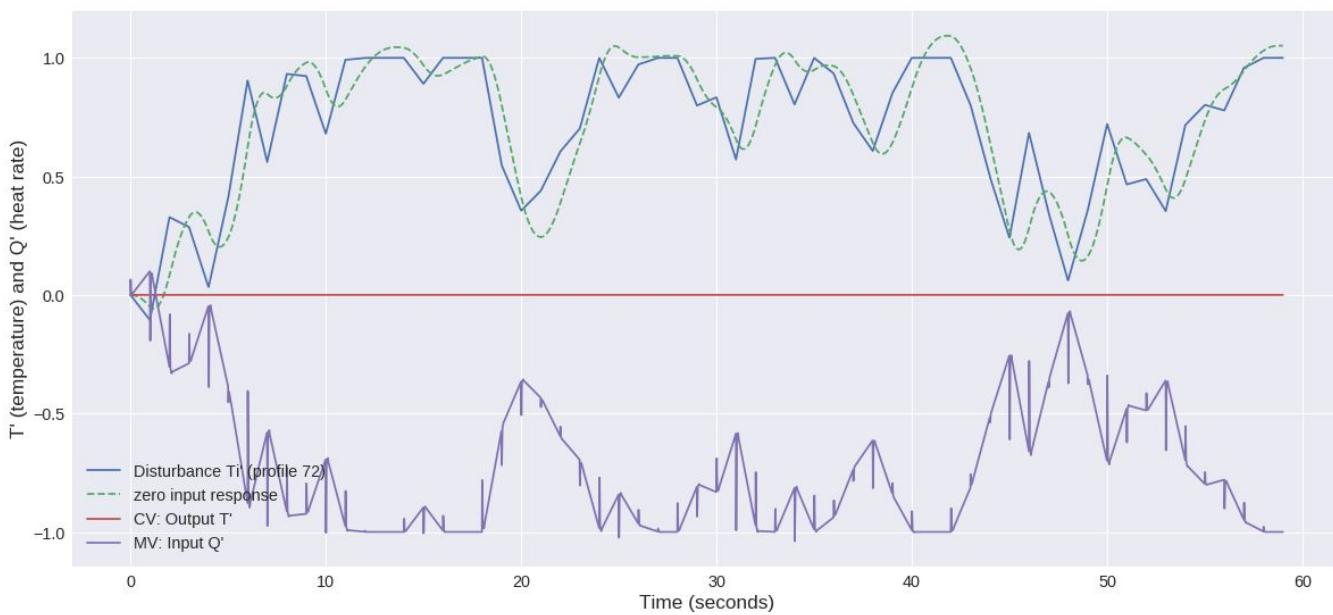
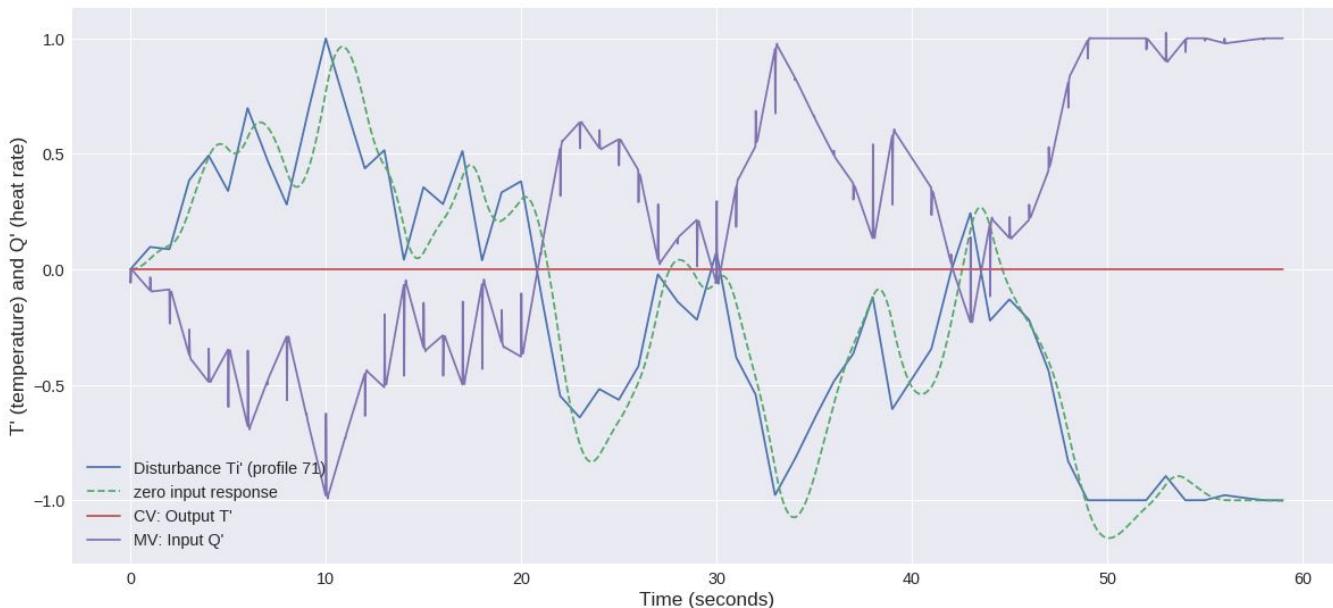


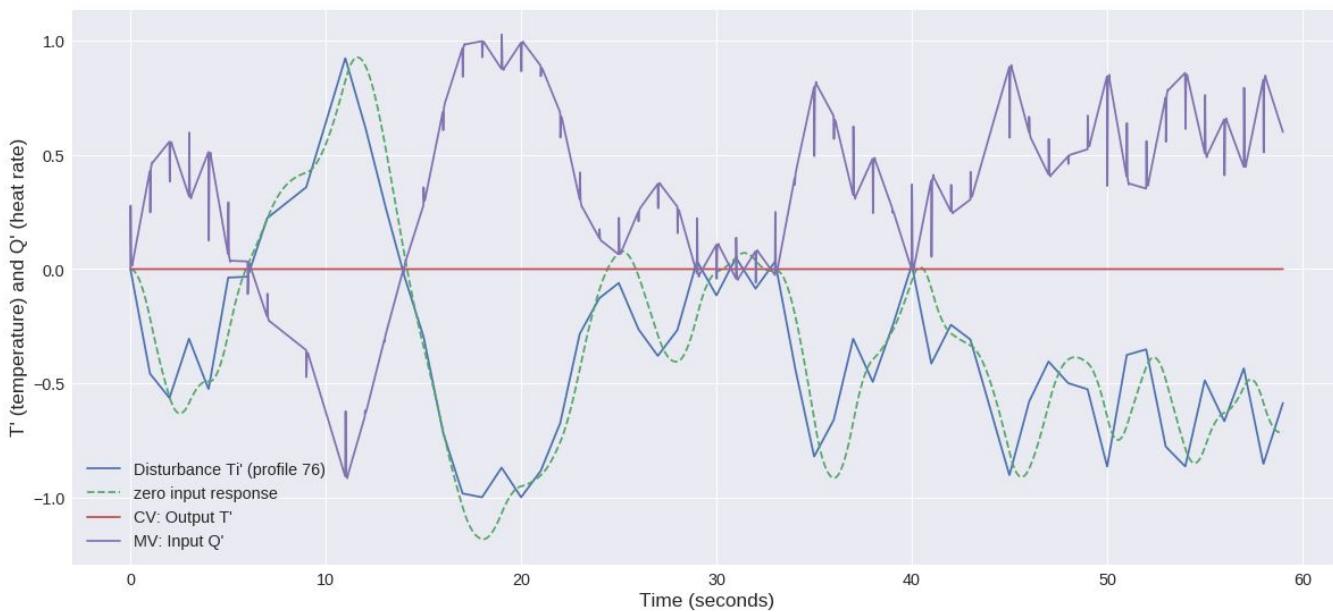
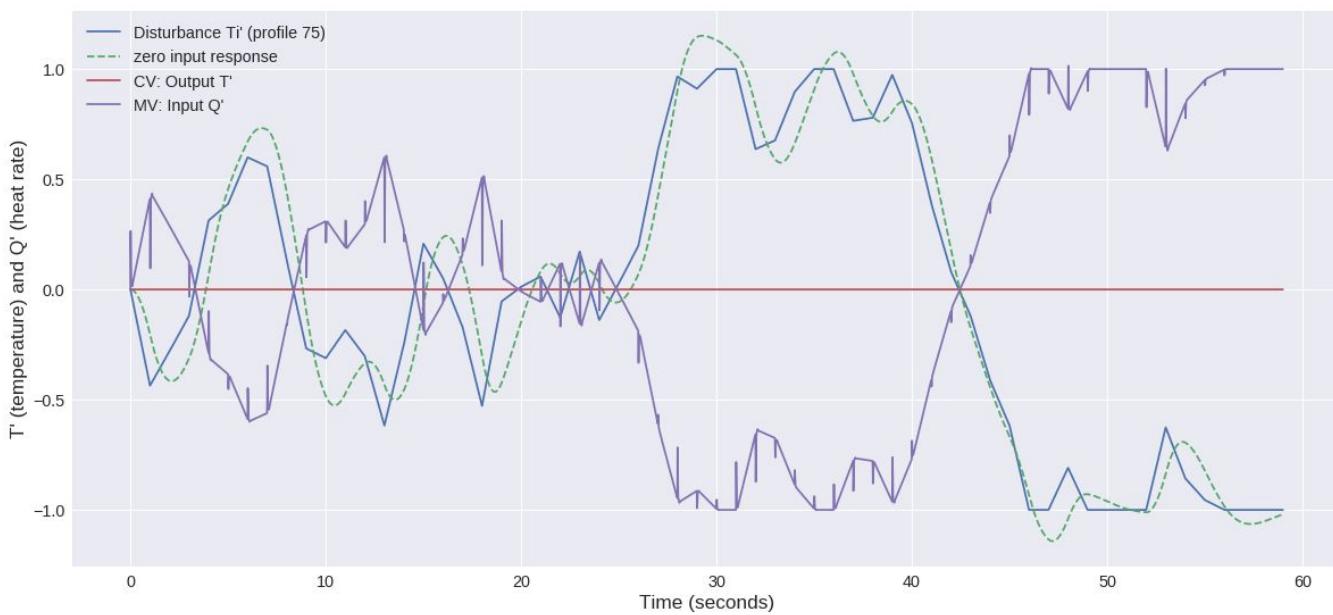
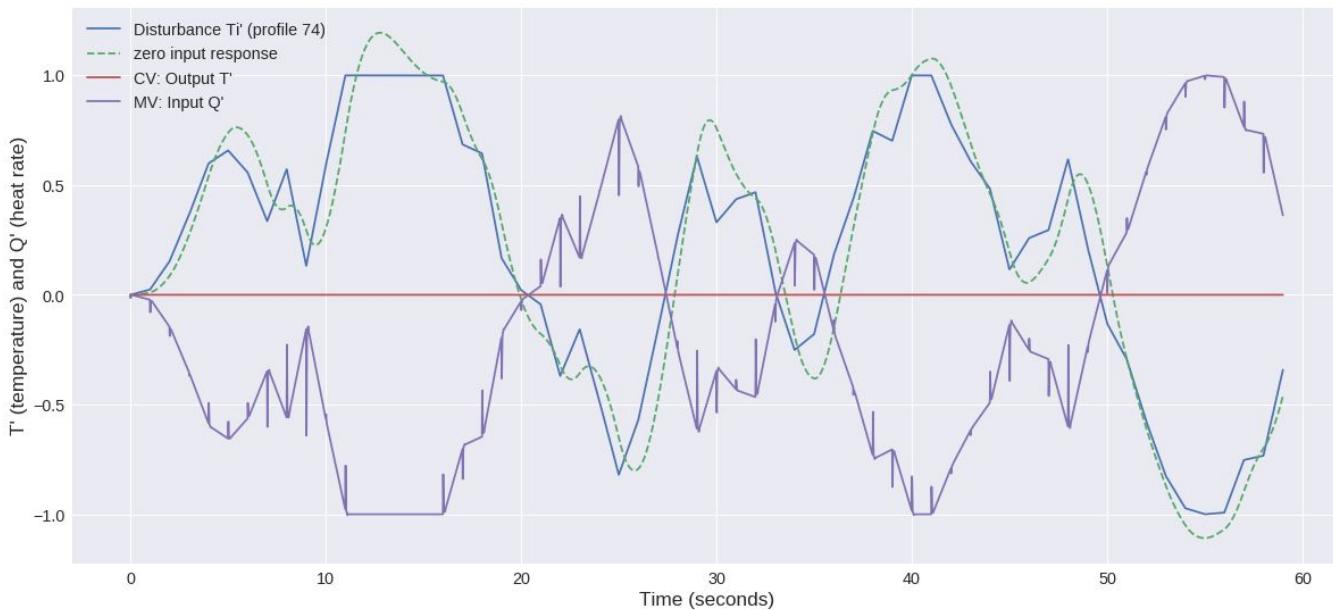


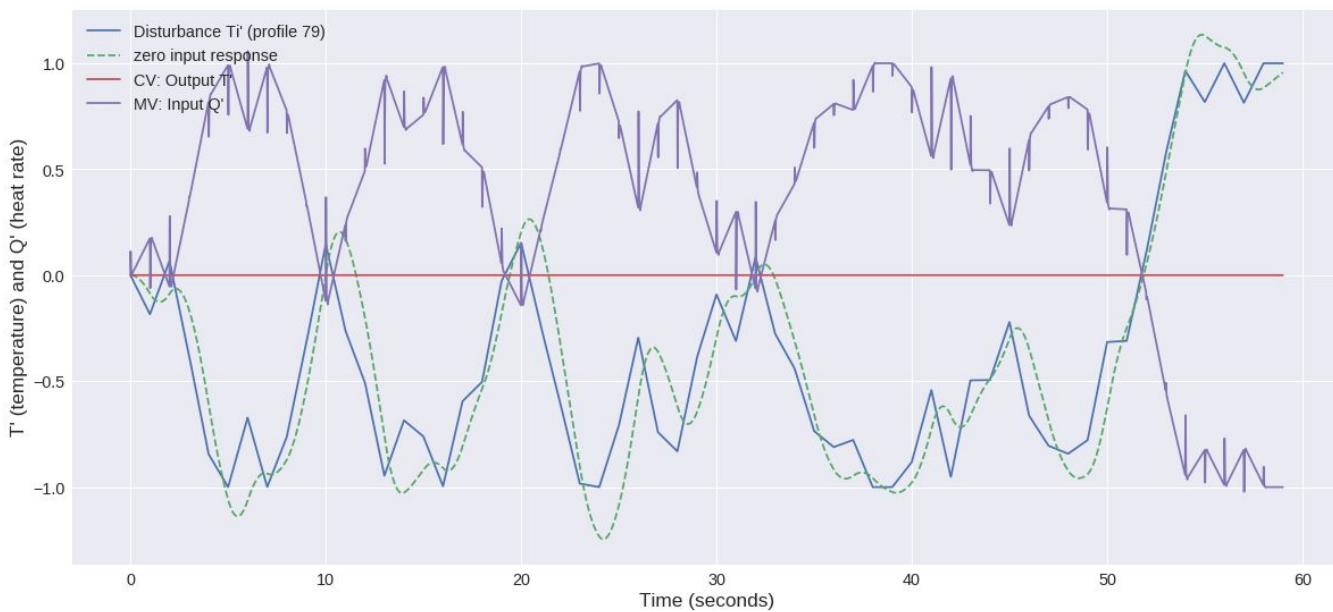
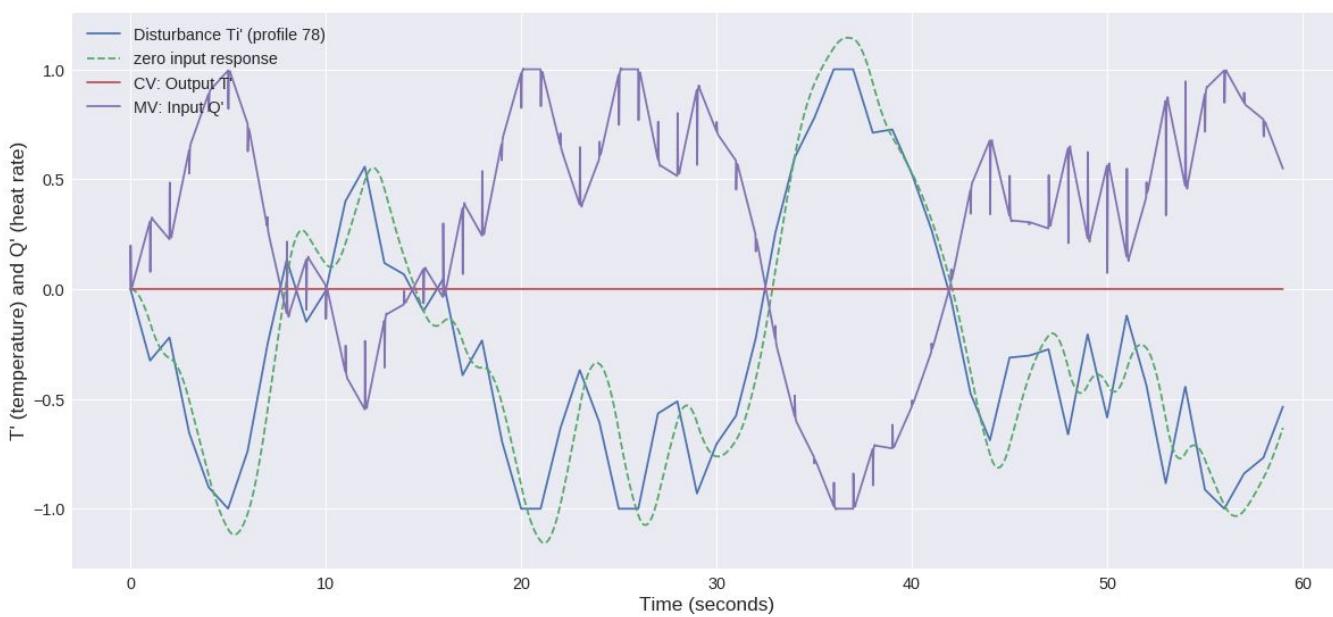
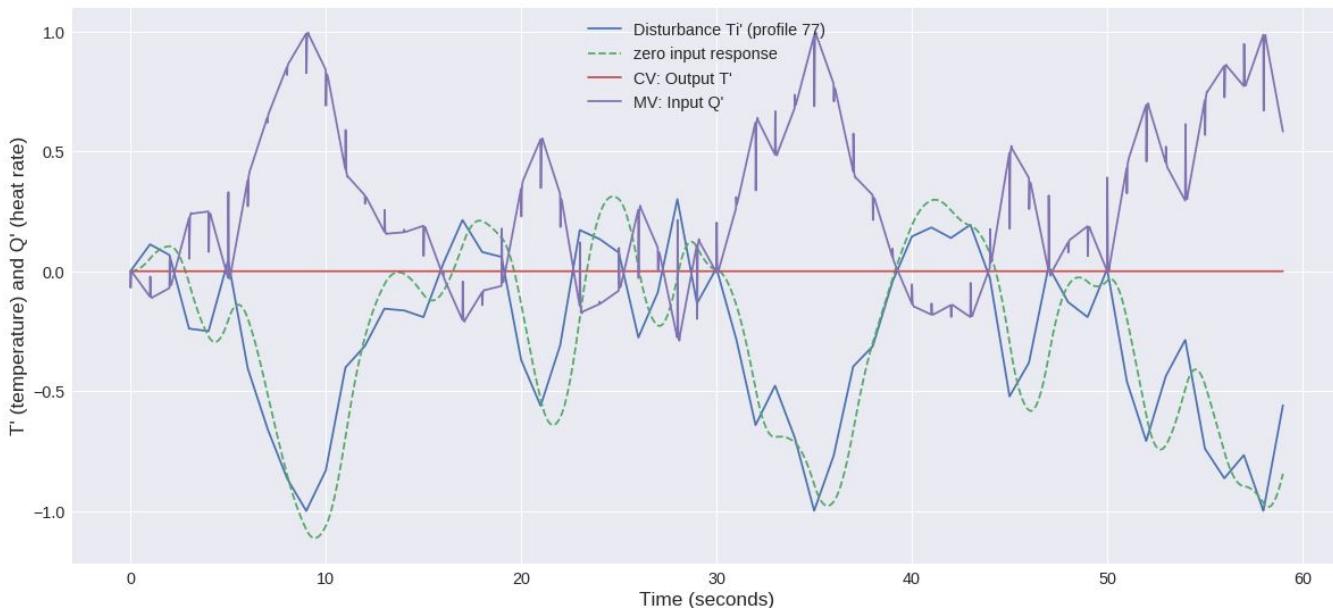


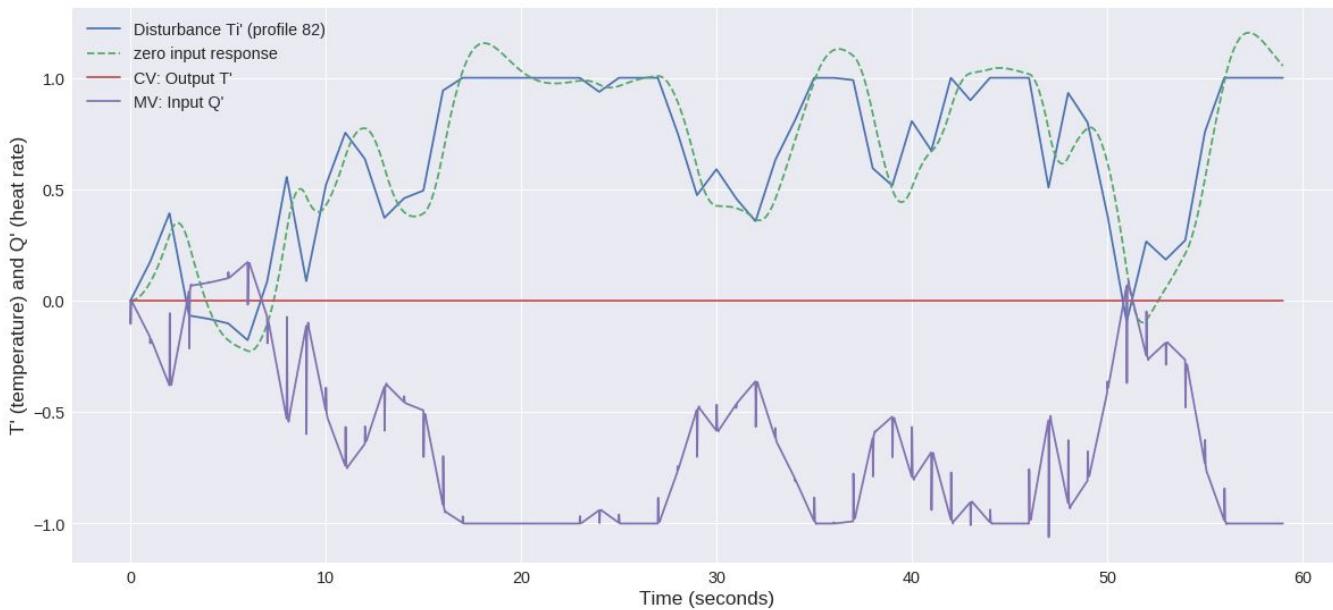
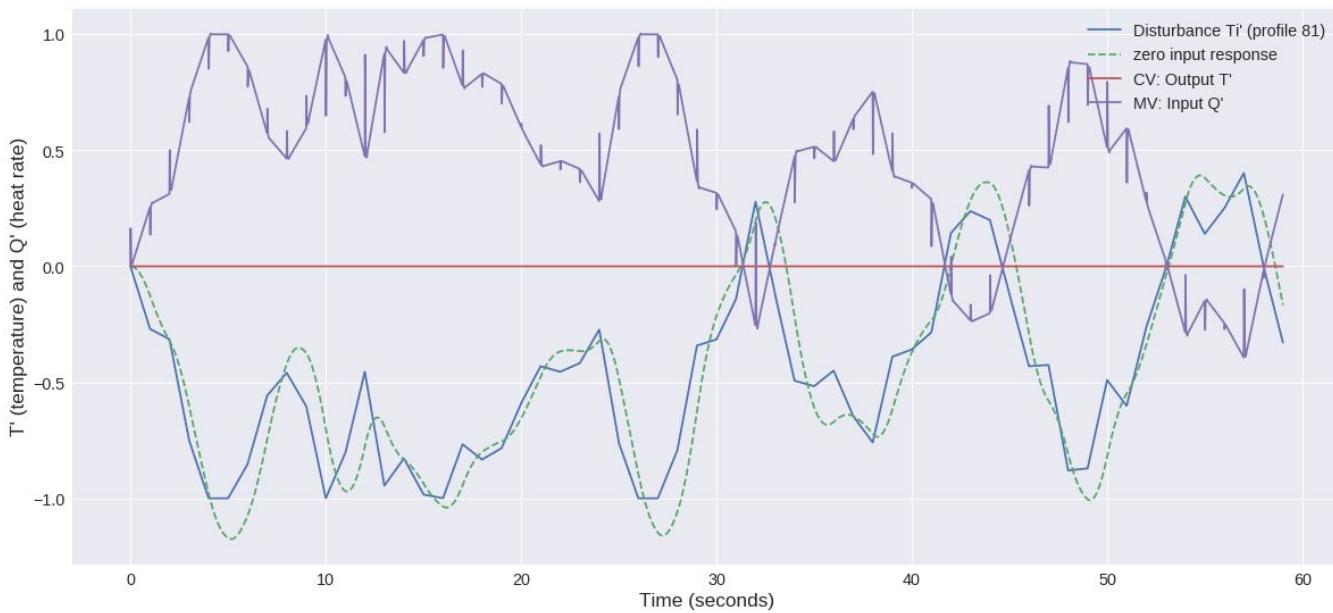
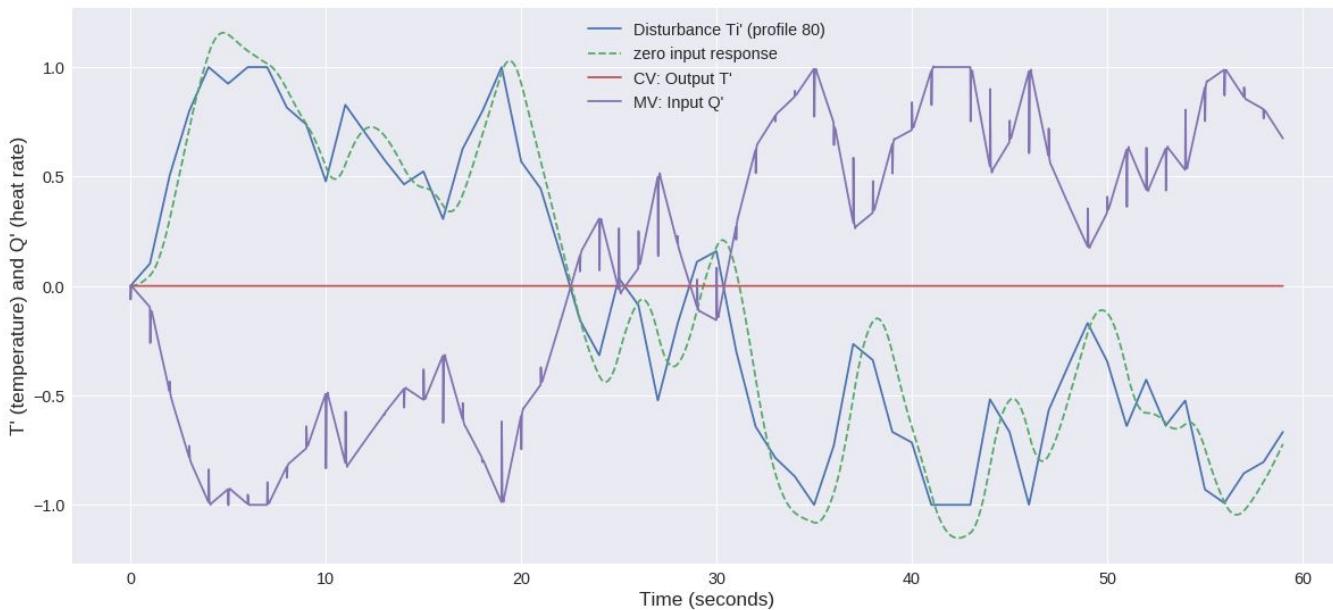


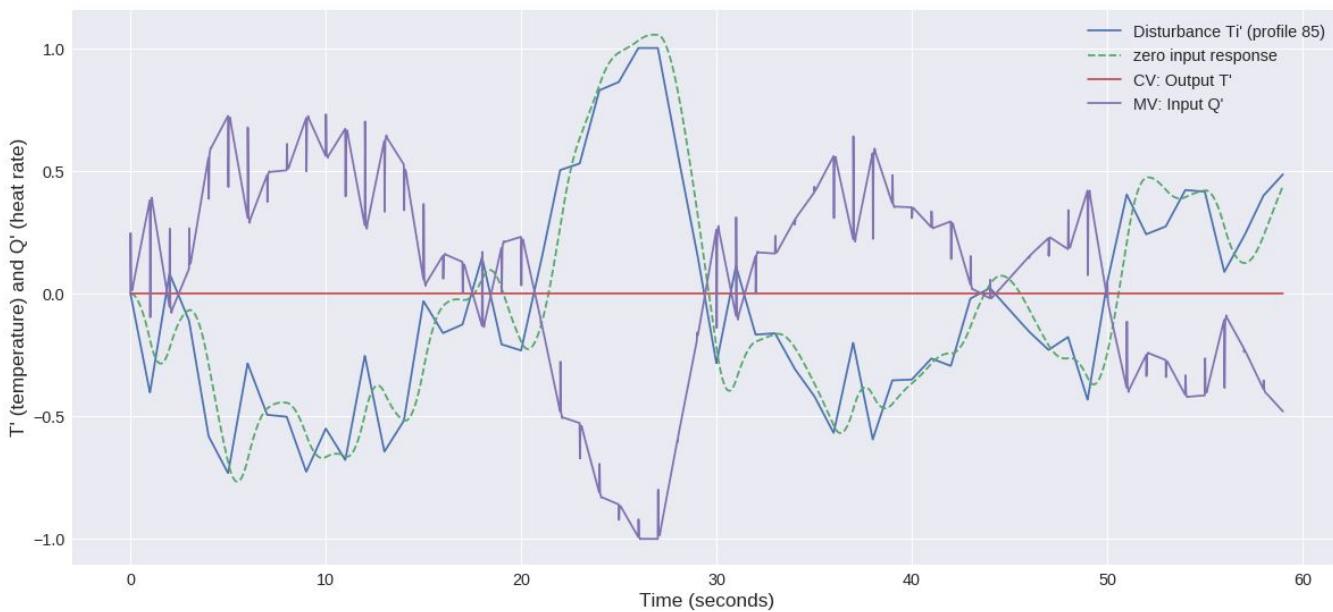
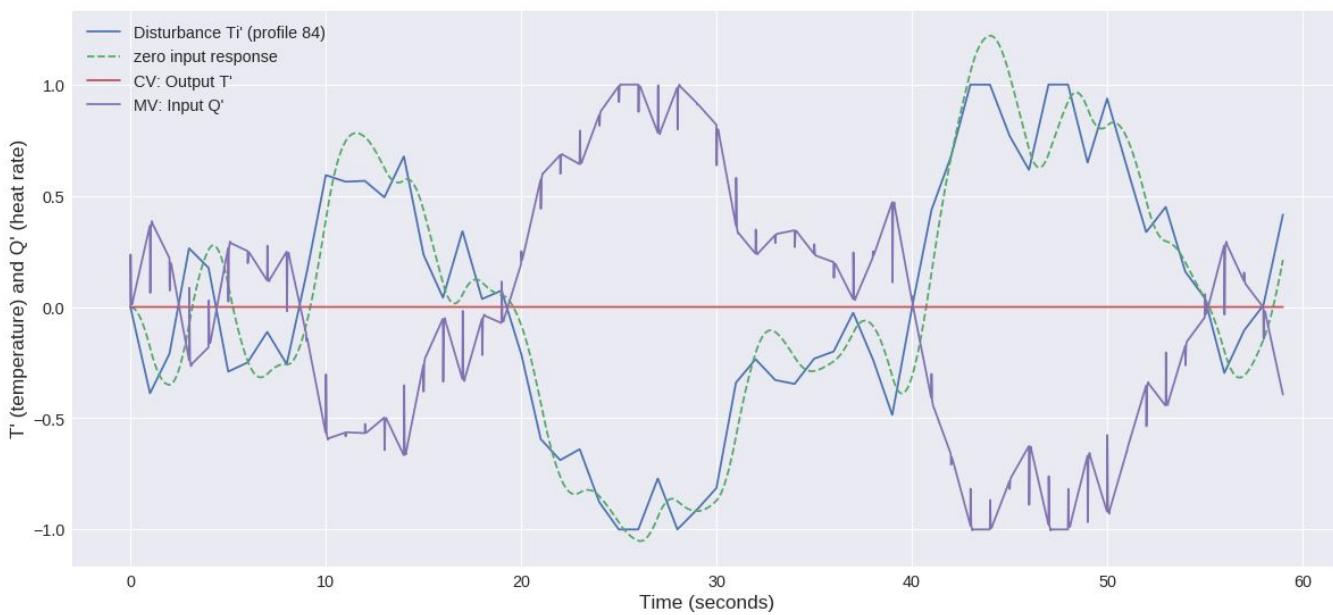
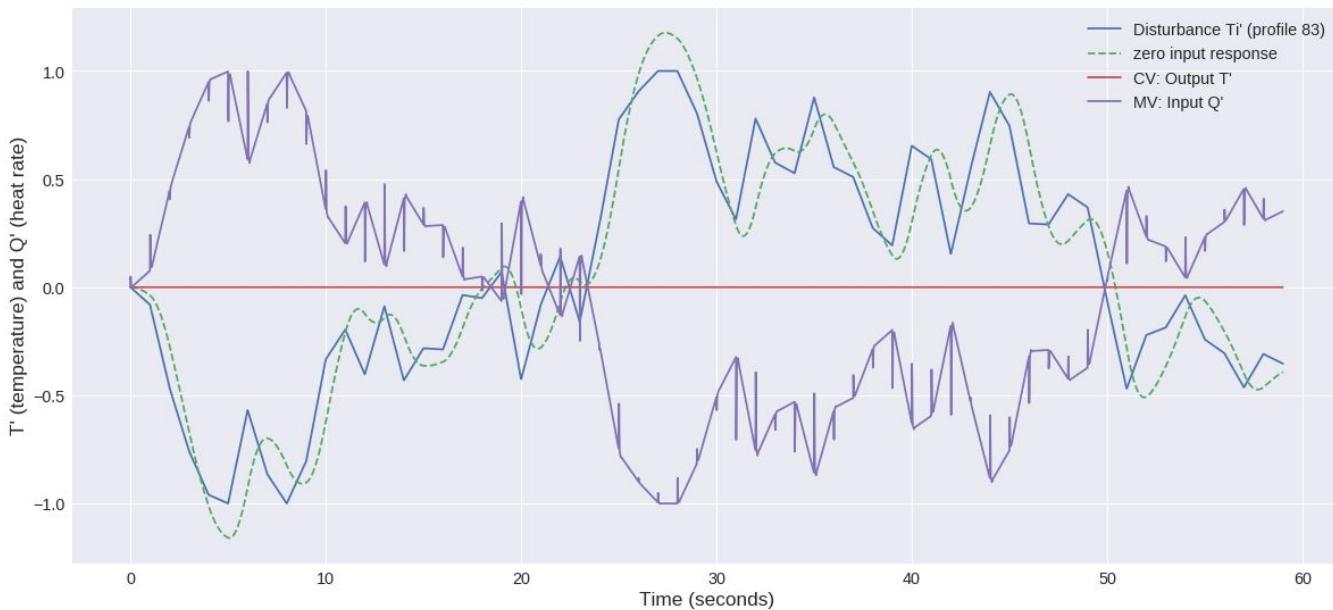


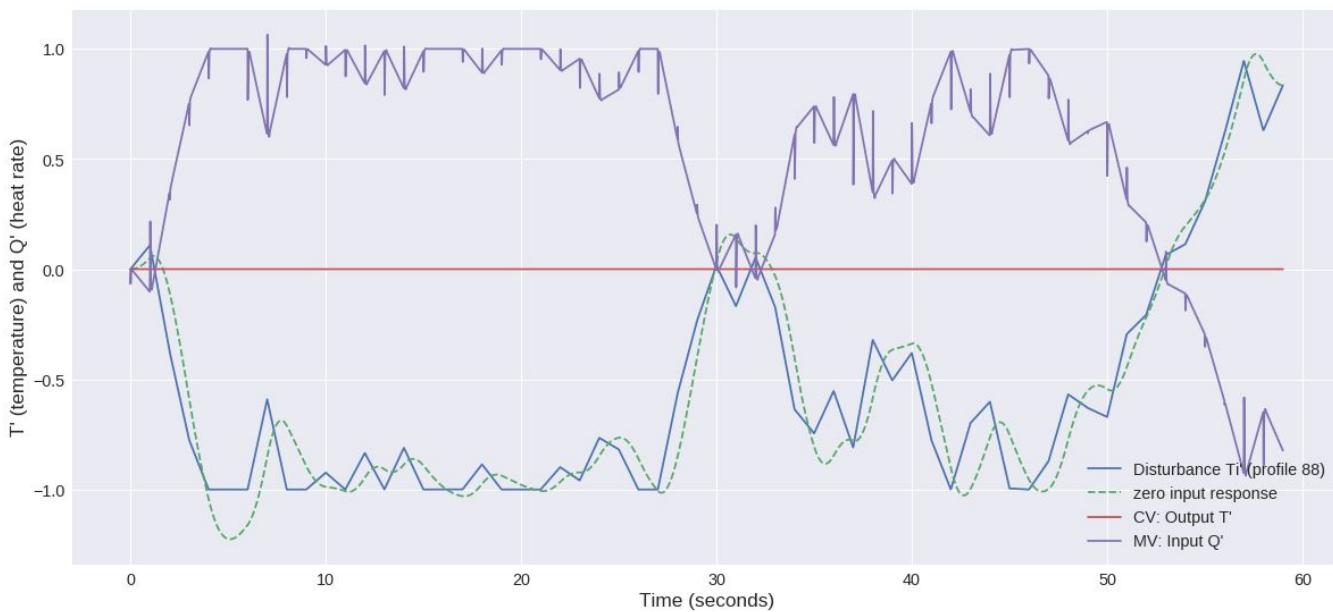
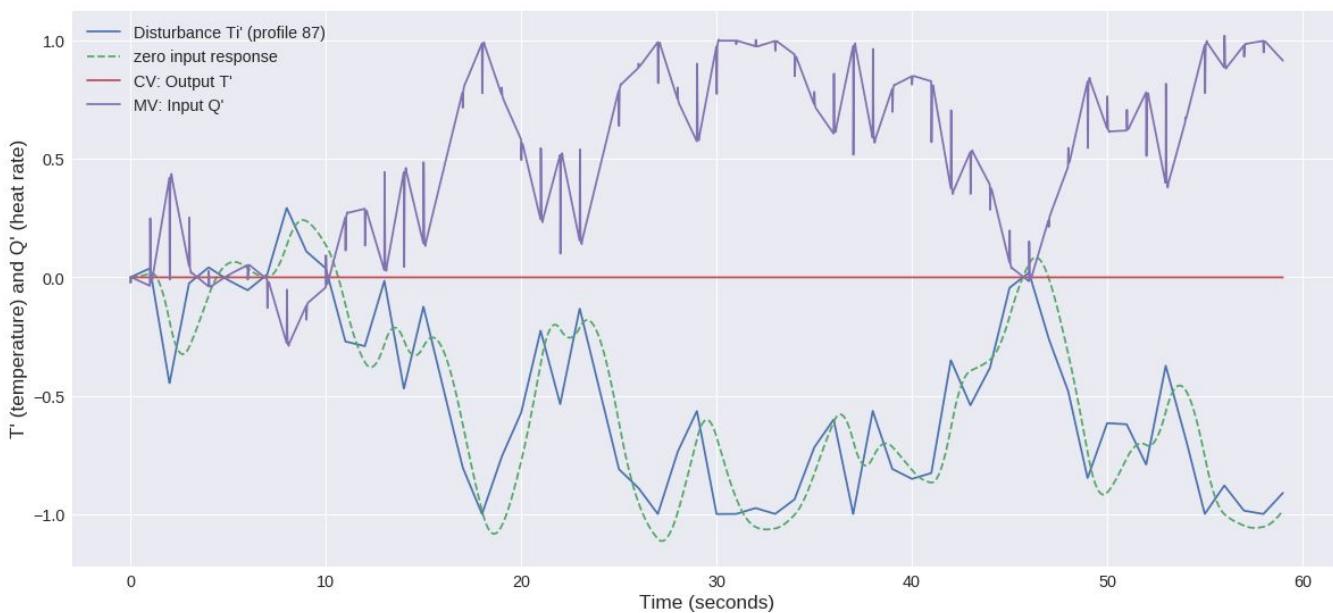
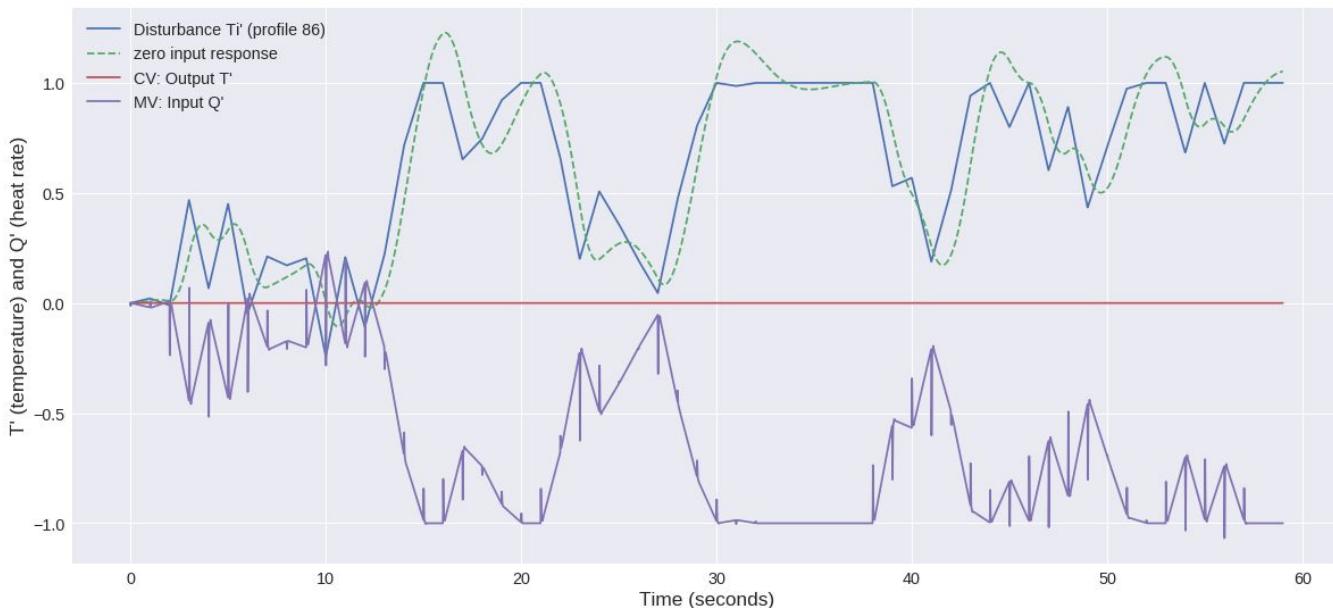


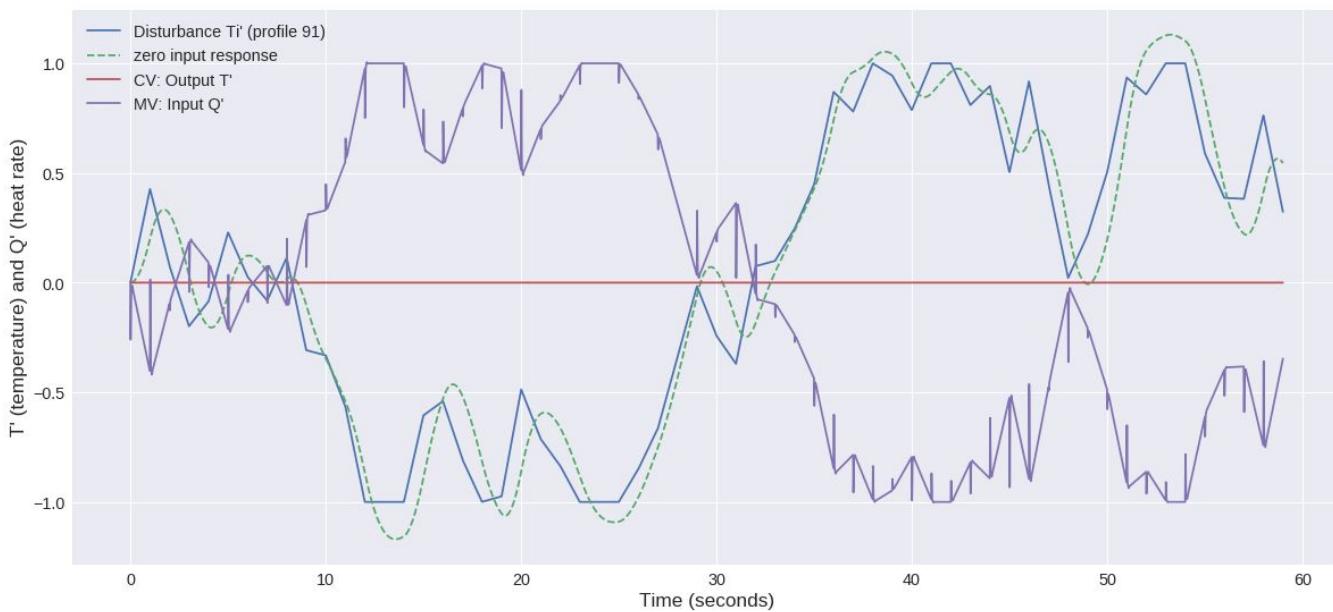
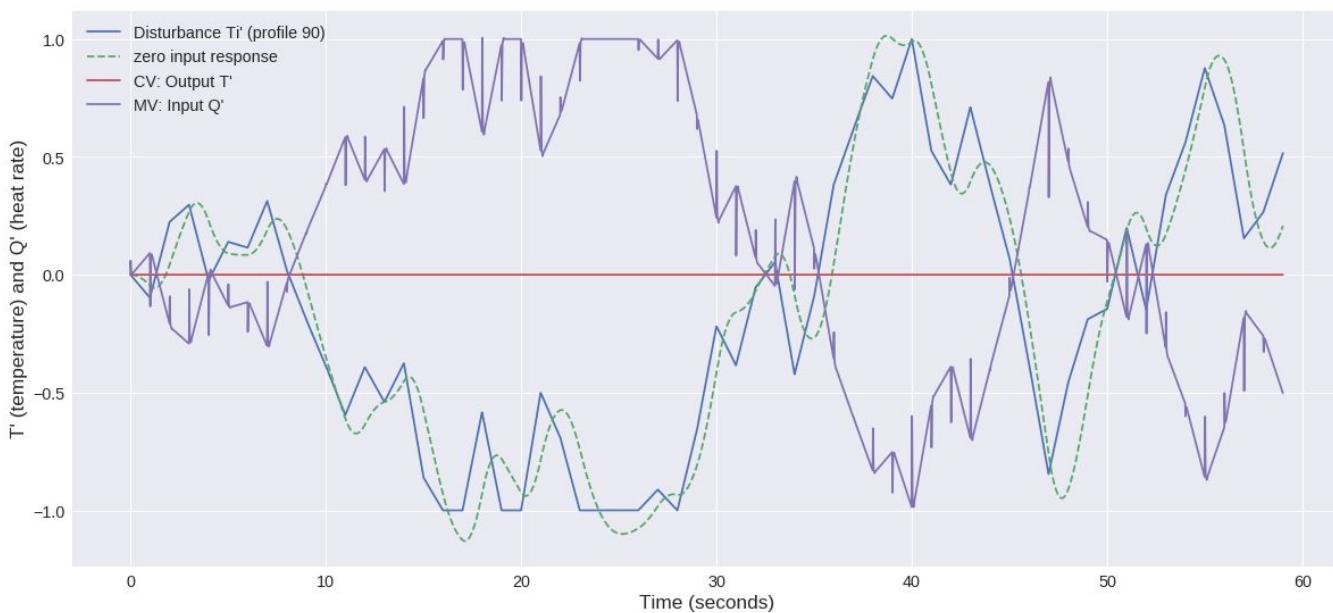
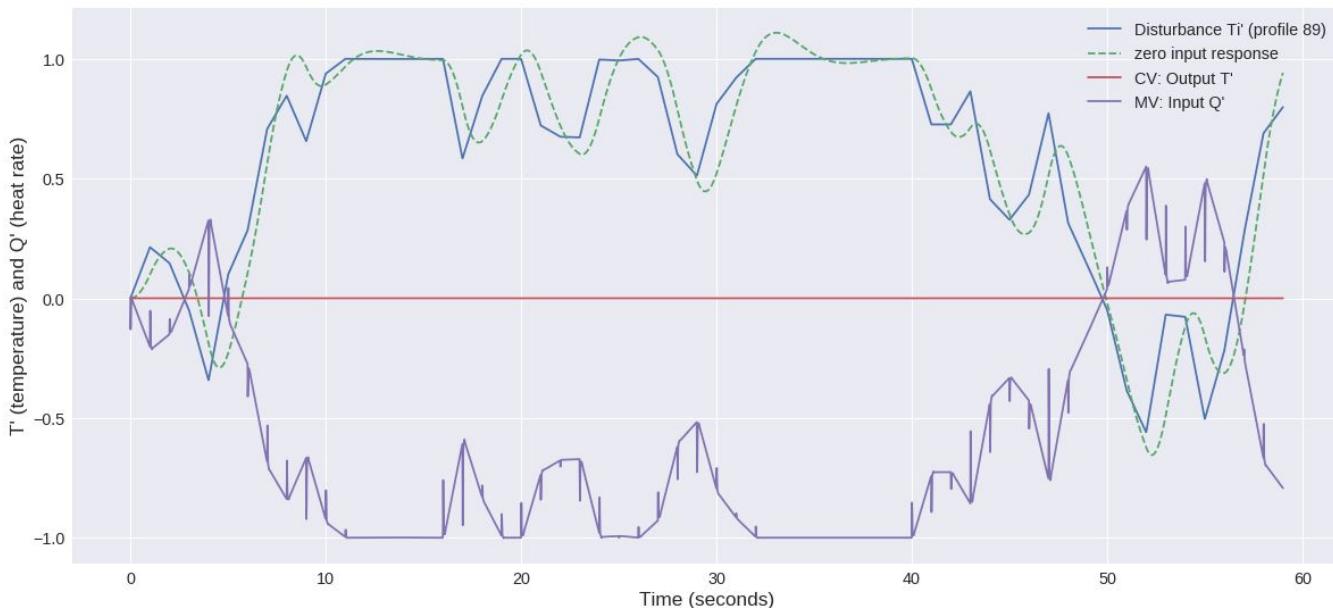


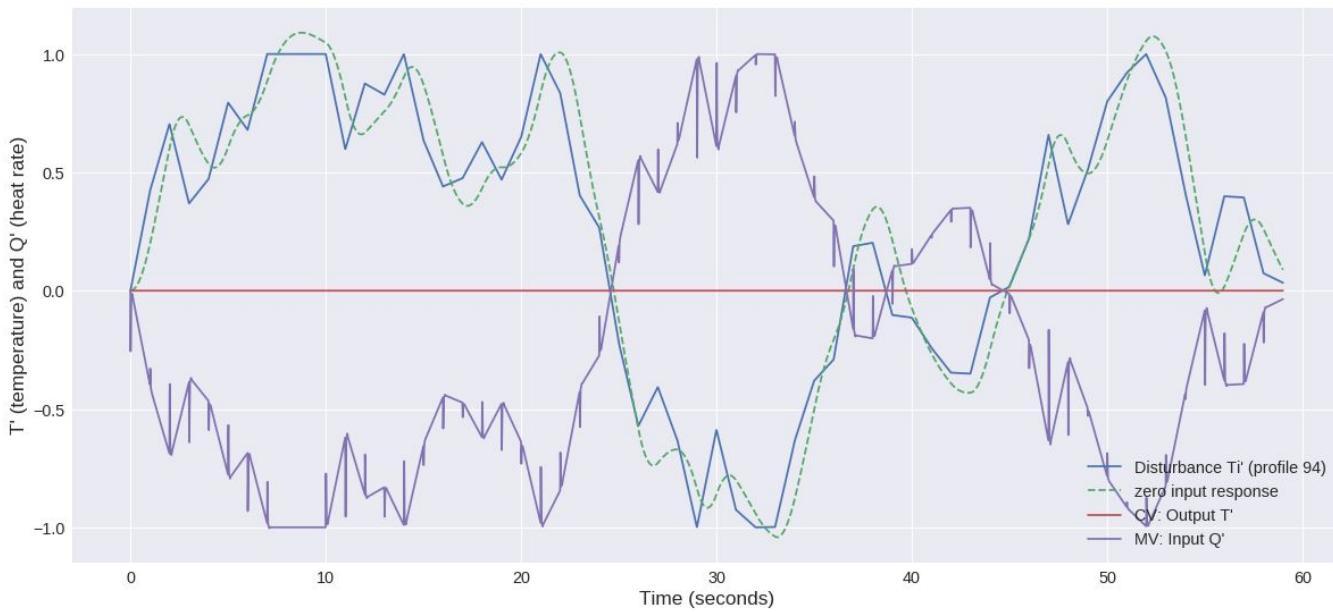
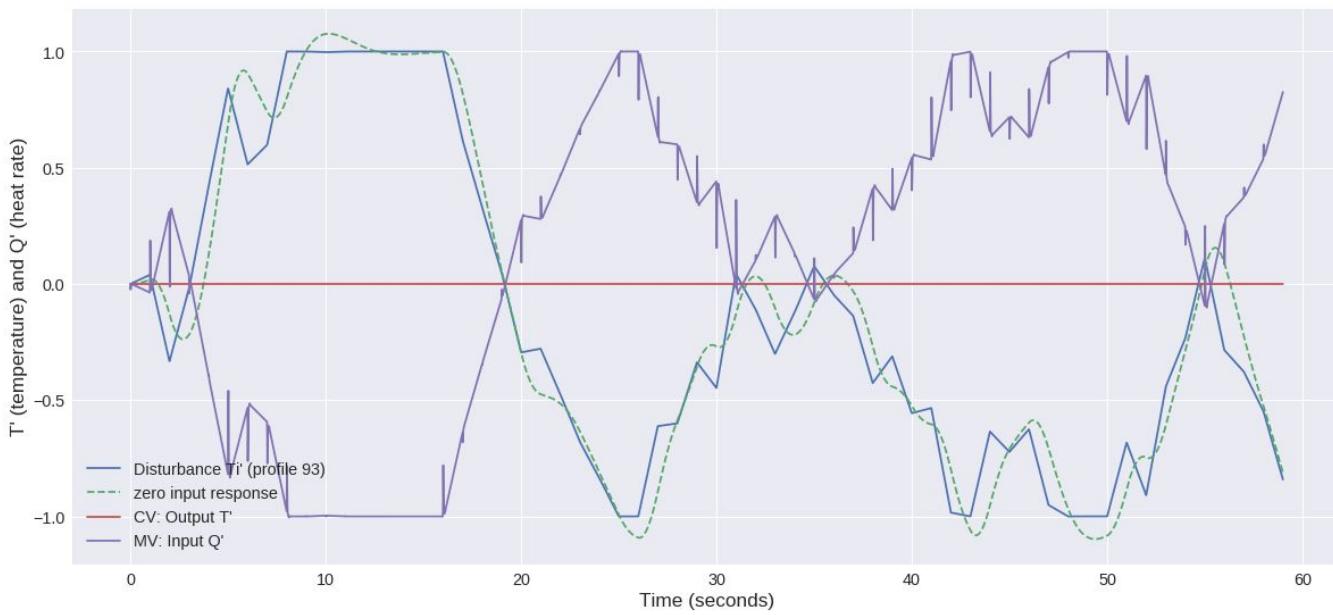
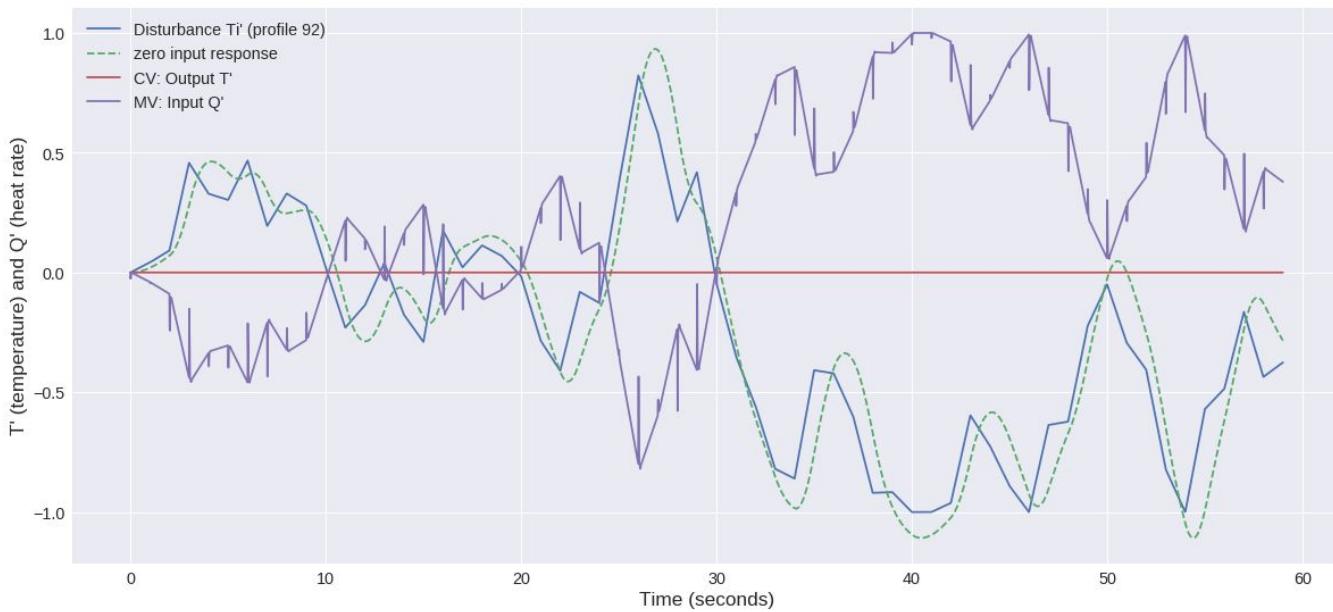


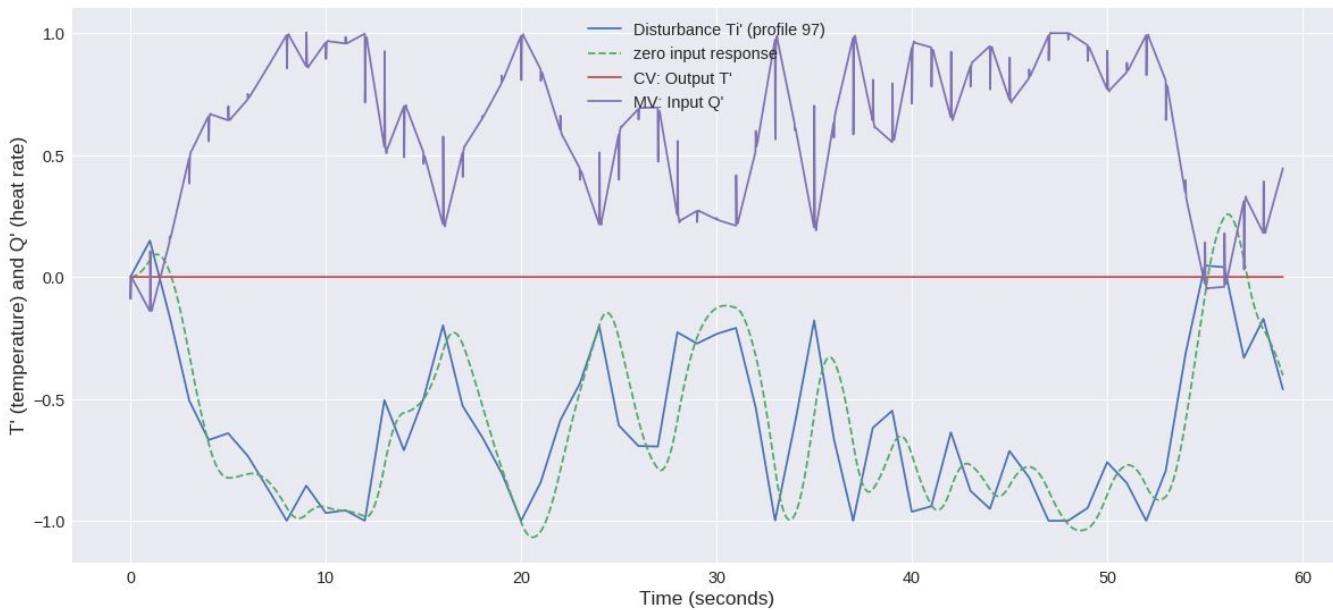
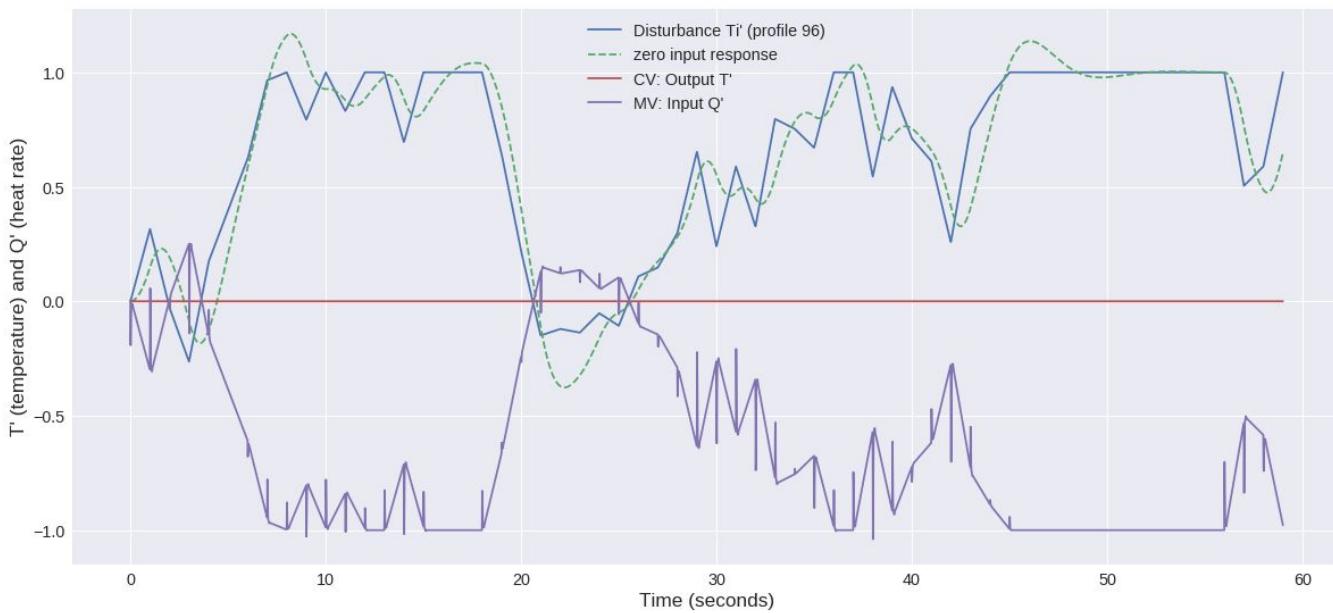
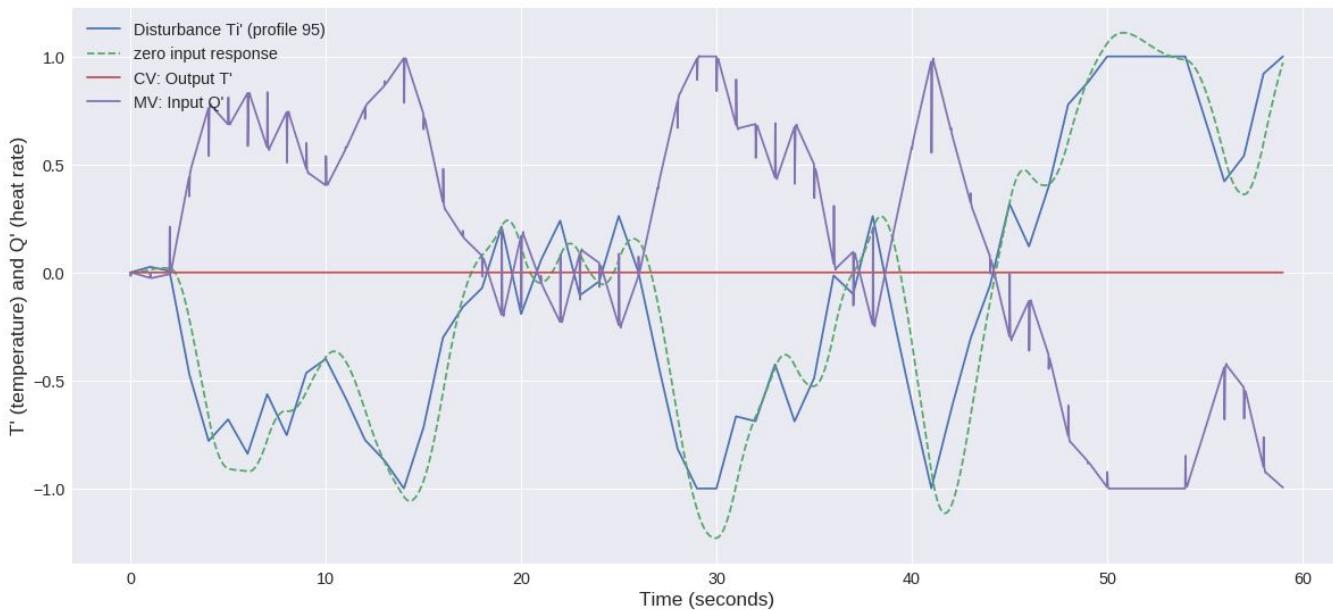


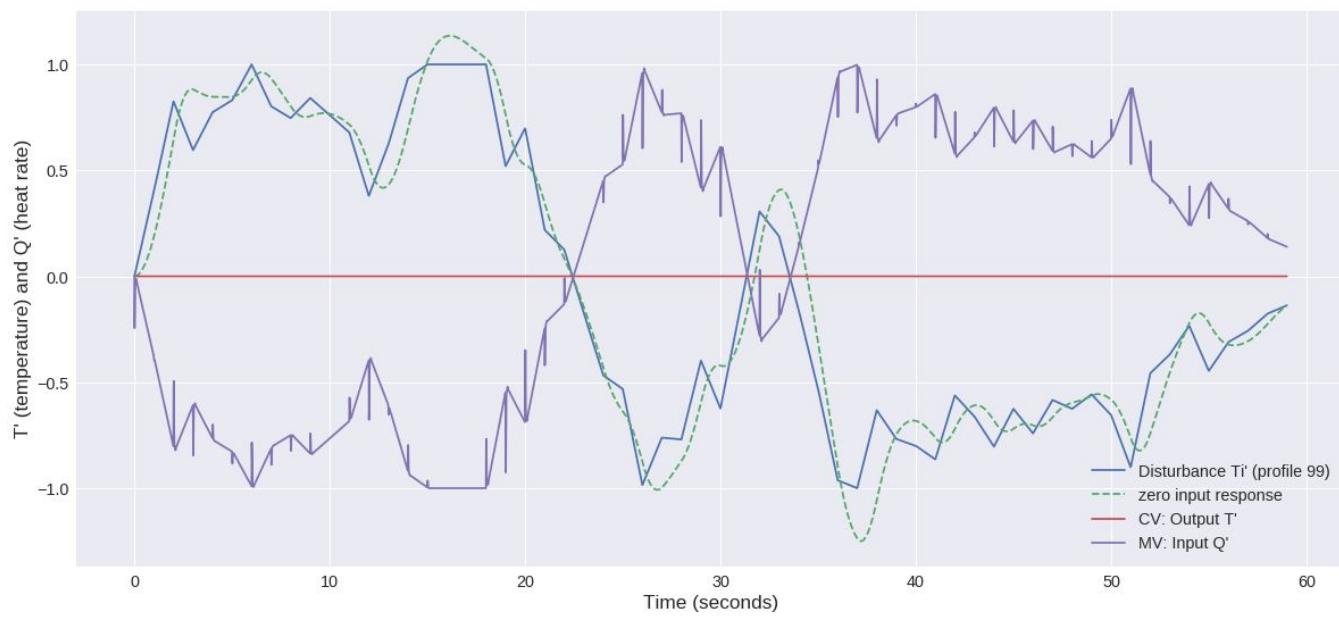
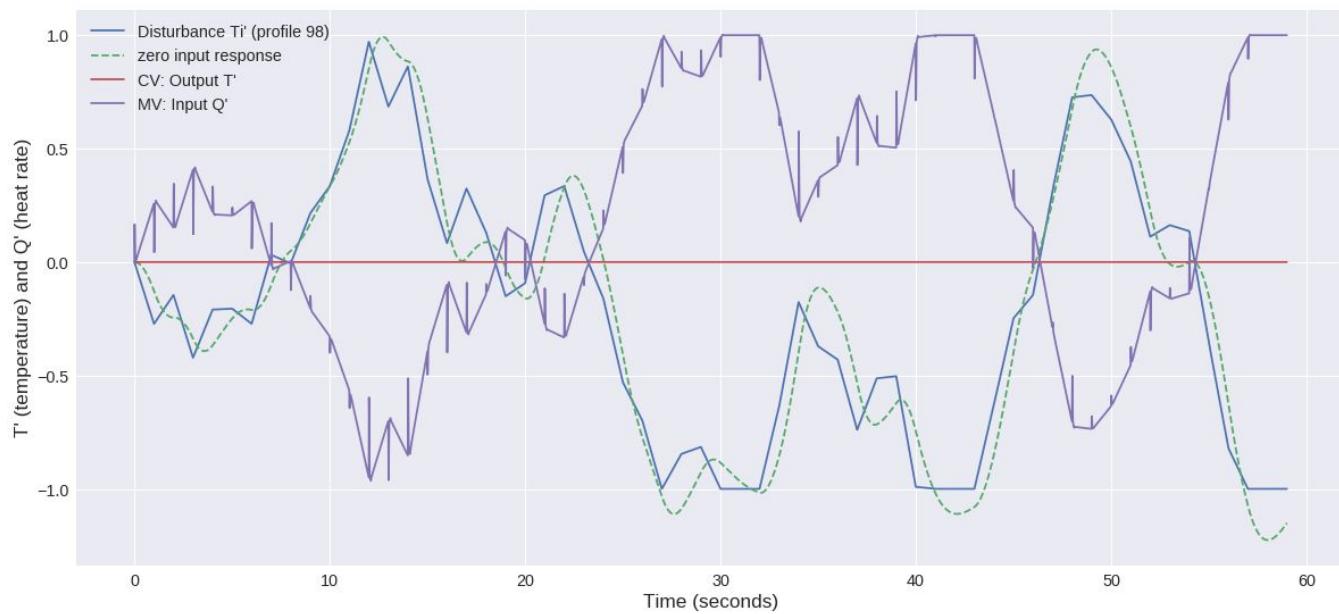










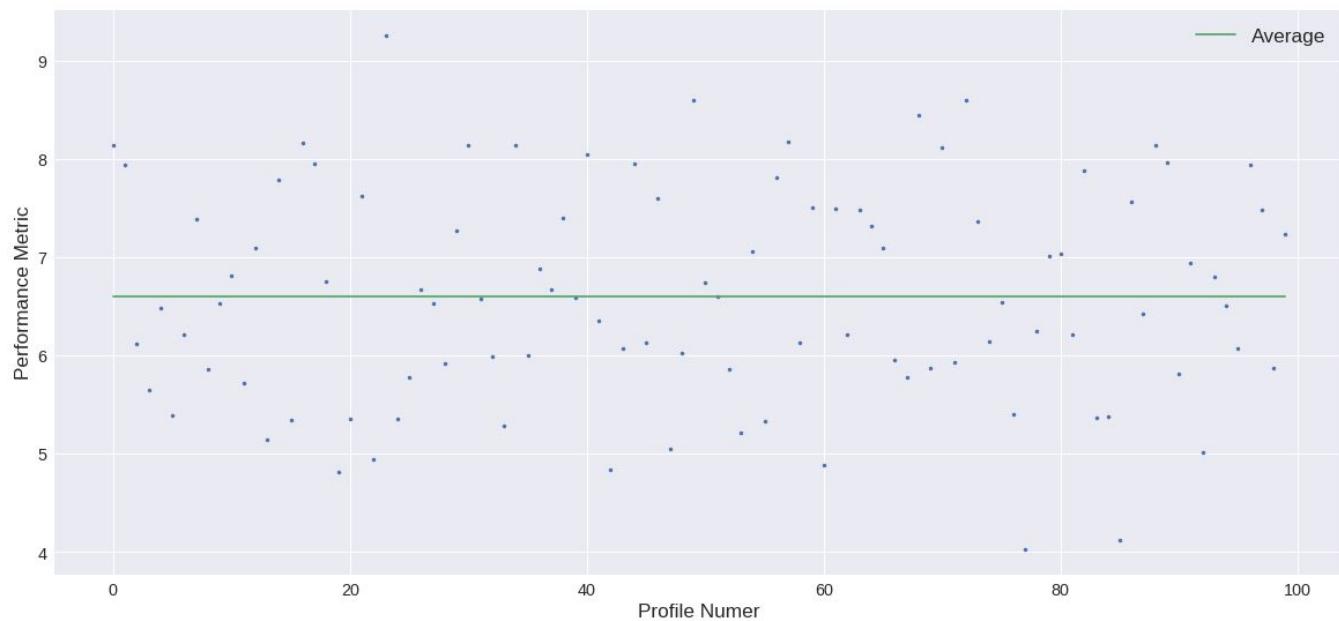


Performance Metric for each disturbance profile:

Minimum value of Perf = 4.033307205120107

Maximum value of Perf = 9.255942643545449

Average value of Perf = 6.603490145150944



Python Code: All codes can be found in [the project's dedicated GitHub](#).

Calculate Performance Metric:

[https://github.com/TimHillmer/CHBE356-data/blob/master/Results/Verify_\(Yankai\).ipynb](https://github.com/TimHillmer/CHBE356-data/blob/master/Results/Verify_(Yankai).ipynb)

This code is nearly identical to the one sent by Yankai. The file input lines have been mildly edited for group use. No numerical calculations have been changed.

Generate plots of CV, MV, DV with respect to time:

[https://github.com/TimHillmer/CHBE356-data/blob/master/Results/Skeleton_\(Masterplan_for_plots\).ipynb](https://github.com/TimHillmer/CHBE356-data/blob/master/Results/Skeleton_(Masterplan_for_plots).ipynb)

All plots in this appendix came from running this code once. Calculations in this code are functionally equal to Yankai's.

Search for optimal tuning parameters:

https://github.com/TimHillmer/CHBE356-data/blob/master/Results/random_search.ipynb

This code randomly searches in user-defined intervals for good parameters, and downloads any that yield a performance metric below a user-defined threshold.

Raw Code Text

Three blank lines are inserted between cells in a notebook. (No cells contain three blank lines in a row.)

Verify (Yankai).ipynb

```
! pip install
git+https://github.com/python-control/python-control@601b58152080d89575cc677474ec7714e1a34ee
2
import control
import numpy as np
from scipy.interpolate import interp1d

NUM_PROFILES = 100
MAX_TIME = 60
T_sp = 0
K_c, tau_I, tau_D, tau_c = [5688.814947611792, 0.000228022206125743, 0.4941522520819933,
0.006245557968152839]

# Disturbance profiles were uploaded to Github so markers can access them through this notebook.
Let's get them.
!rm -rf CHBE356-data
!git clone https://github.com/TimHillmer/CHBE356-data/

# obtain a numerically ordered list of the paths to the disturbance profiles
import glob
filenames = glob.glob('CHBE356-data/Disturbance_profiles/*.csv')
filenames.sort()

# obtain an array containing all disturbance profiles (data in [profile#, timevalue] format)
import pandas as pd
df = pd.concat([pd.read_csv(files).transpose() for files in filenames], ignore_index = True)
# each disturbance profile is a *row*
Ti_data = df.values

def simulate(i, K_c, tau_I, tau_D, tau_c):
    time_data = np.linspace(0, MAX_TIME-1, MAX_TIME)
    T_i_data = Ti_data[i]
    f = interp1d(time_data, T_i_data)
    points_per_seond = 100
    time = np.linspace(0, MAX_TIME-1, MAX_TIME*points_per_seond)
    T_i = f(time)
```

```

s = control.tf([1,0],[0,1])
G_p = 1/(s**2 + s + 1)
G_d = (s+1)/(s**2 + s + 1)
G_c = K_c * (1+ 1/(tau_l*s) + (tau_D*s)/(tau_c*s + 1))
sys_D = G_d / (1 + G_p * G_c)

Tsp = 0
_, T, _ = control.forced_response(sys_D, time, T_i)
_, Q, _ = control.forced_response(G_c, time, Tsp - T)
error = (sum(abs(T)) + 0.2*sum(abs(Q)))/points_per_seond
if sum(abs(T))>= 5 or sum(abs(Q))>= 5:
    error = 1e6
return error

total_error = 0
for i in range(NUM_PROFILES):
    error = simulate(i, K_c, tau_l, tau_D, tau_c)
    total_error += error
print(f'Average error: {total_error / NUM_PROFILES}')

```

Skeleton (Masterplan for plots).ipynb

```
# Disturbance profiles were uploaded to Github so markers can access them through this notebook.  
Let's get them.  
!rm -rf CHBE356-data  
!git clone https://github.com/TimHillmer/CHBE356-data/  
  
# obtain a numerically ordered list of the paths to the disturbance profiles  
import glob  
filenames = glob.glob('CHBE356-data/Disturbance_profiles/*.csv')  
filenames.sort()  
  
# obtain an array containing all disturbance profiles (data in [profile#, timevalue] format)  
import numpy as np  
import pandas as pd  
df = pd.concat([pd.read_csv(files).transpose() for files in filenames], ignore_index = True)  
# each disturbance profile is a *row*  
  
# define Yankai's 100 point interpolation  
from scipy.interpolate import interp1d  
Ti_data = df.values  
time_data = np.arange(len(Ti_data[0])) # assume Ti' data is given at each second  
f = interp1d(time_data, Ti_data)  
points_per_second = 100  
time = np.linspace(time_data[0], time_data[-1], len(time_data)*points_per_second)  
TiPrimes = f(time)  
  
# Any remaining install/imports here  
! pip install  
git+https://github.com/python-control/python-control@601b58152080d89575cc677474ec7714e1a34ee  
2  
import control  
import matplotlib.pyplot as plt  
  
  
def masterplan(KC, TauL, TauD, TauC, plots=True, summary=True, failwarning=True):  
    s = control.tf([1,0],[0,1]) # Define the s variable  
    Gd = (s+1) / (s**2+s+1) # T' / Ti' (disturbance) transfer function  
    Gp = 1 / (s**2+s+1) # T' / Q' (process) transfer function  
    Gc = KC*(1 + 1/(TauL*s) + TauD*s/(TauC*s+1)) # Controller transfer function  
  
    Gtotal = Gd / (1 + Gp*Gc) # no term for (temperature deviation) setpoint because it is always zero  
  
    if plots or summary:
```

```

plt.style.use('seaborn') # plot style for if 'plots' or 'summary' are marked True
params = {'legend.fontsize': 'x-large',
           'figure.figsize': (20, 9),
           'axes.labelsize': 'x-large',
           'axes.titlesize':'x-large',
           'xtick.labelsize':'large',
           'ytick.labelsize':'large'}
plt.rcParams.update(params)

Perf = np.zeros(len(TiPrimes)) # array to store Perf for each disturbance profile
for i in range(len(TiPrimes)): # main loop for calculation and plotting
    # T' response including controller
    t, Tprime, x = control.forced_response(Gtotal, time, TiPrimes[i])

    # controller response to error (=input)
    t, Qprime, x = control.forced_response(Gc, time, -Tprime)

    Perf[i] = (sum(np.absolute(Tprime)) + 0.2*sum(np.absolute(Qprime)))/points_per_second
    # performance metric for each profile

if plots == True: # plot results from the forced_repsonse calculations. Delete the dashed lines
when submitting.
    plt.plot(time, TiPrimes[i], label = f"Disturbance Ti' (profile {i})") # disturbance signal

    # response to disturbance (as if there were no controller)
    t, zero, x = control.forced_response(Gd, time, TiPrimes[i])
    plt.plot(t, zero, '--', label = 'zero input response')

    plt.plot(t, Tprime, label = "CV: Output T") # output value used for performance metric
    plt.plot(t, Qprime, label = "MV: Input Q") # input value used for performance metric

    # T' response to input (as if disturbance were always =0)
    # t, ideal, x = control.forced_response(Gp, time, Qprime)
    # plt.plot(t, ideal, '--', label = 'response to input') # should be output minus disturbance response

    plt.legend(fontsize='large')
    plt.xlabel('Time (seconds)')
    plt.ylabel("T' (temperature) and Q' (heat rate)")
    plt.show()

if summary == True: # prints parameters, three-point summary, and a "density" distribution
    print(f'Variables:\nKC = {KC},\nTauI = {TauI},\nTauD = {TauD},\nTauC = {TauC}\n')
    print('Minimum value of Perf = ', min(Perf))
    print('Maximum value of Perf = ', max(Perf))
    print('Average value of Perf = ', np.average(Perf))
    plt.plot(Perf, '.')
    plt.plot(np.arange(len(TiPrimes)), np.full(len(TiPrimes),np.average(Perf)), label = 'Average')

```

```
plt.xlabel('Profile Numer')
plt.ylabel("Performance Metric")
plt.legend()
plt.show()

if failwarning and ( any(abs(Tprime)>5) or any(abs(Qprime)>5) ): # failure condition defined by
project statement
    print(f'The case ({KC}, {TauI}, {TauD}, {TauC}) will score you an automatic ZERO')

return np.average(Perf)
```

```
A = masterplan(5688.814947611792, 0.0002280222206125743, 0.4941522520819933,
0.006245557968152839)
```

```
print(f'Average error is {A}')
```

```
# Disturbance profiles were uploaded to Github so markers can access them through this notebook.  
Let's get them.  
!rm -rf CHBE356-data  
!git clone https://github.com/TimHillmer/CHBE356-data/  
  
# obtain a numerically ordered list of the paths to the disturbance profiles  
import glob  
filenames = glob.glob('CHBE356-data/Disturbance_profiles/*.csv')  
filenames.sort()  
  
# obtain an array containing all disturbance profiles (data in [profile#, timevalue] format)  
import numpy as np  
import pandas as pd  
df = pd.concat([pd.read_csv(files).transpose() for files in filenames], ignore_index = True)  
# each disturbance profile is a *row*  
  
# define Yankai's 100 point interpolation  
from scipy.interpolate import interp1d  
Ti_data = df.values  
time_data = np.arange(len(Ti_data[0])) # assume Ti' data is given at each second  
f = interp1d(time_data, Ti_data)  
points_per_second = 100  
times = np.linspace(time_data[0], time_data[-1], len(time_data)*points_per_second)  
TiPrimes = f(times)  
  
# Any remaining install/imports here  
! pip install  
git+https://github.com/python-control/python-control@601b58152080d89575cc677474ec7714e1a34ee  
2  
import control  
import matplotlib.pyplot as plt  
import random  
  
def fasterplan(KC, TauL, TauD, TauC, s, times, Gd, Gp): # streamlined version to save precious  
milliseconds each run  
    Gc = KC*(1 + 1/(TauL*s) + TauD*s/(TauC*s+1)) # Controller transfer function  
    Gtotal = Gd / (1 + Gp*Gc) # no term for (temperature deviation) setpoint because it is always zero  
    Perf = np.zeros(len(TiPrimes)) # array to store Perf for each disturbance profile  
    for i in range(len(TiPrimes)): # main loop for calculation and plotting  
        # T' response including controller  
        t, Tprime, x = control.forced_response(Gtotal, times, TiPrimes[i])
```

```

# controller response to error (=input)
t, Qprime, x = control.forced_response(Gc, times, -Tprime)

Perf[i] = (sum(np.absolute(Tprime)) + 0.2*sum(np.absolute(Qprime)))/points_per_second
# performance metric for each profile
return np.average(Perf)

def lograndom(lo, hi): # samples from log(X), where X in uniformly distributed within the provided
bounds
    return(lo*10**(random.uniform(0, np.log10(hi/lo)))) 

# initial information for use in "fasterplan"
s = control.tf([1,0],[0,1]) # Define the s variable
Gd = (s+1) / (s**2+s+1) # T' / Ti' (disturbance) transfer function
Gp = 1 / (s**2+s+1) # T' / Q' (process) transfer function

Ntests = 500
Nhappy = int(Ntests/10)

counter = 0
happycounter = 0

data = np.zeros((Ntests, 5))
happydata = np.zeros((Nhappy, 5))
from google.colab import files

for i in range(Ntests):
    Kc = lograndom(1e3, 1e4)
    Ti = lograndom(1e-4, 1e-3)
    Td = lograndom(0.05,1.5)
    Tc = lograndom(5e-4, 0.1)

    Perf = fasterplan(Kc, Ti, Td, Tc, s, times, Gd, Gp)
    if Perf <= 6.95:
        happydata[happycounter] = np.array([Perf, Kc, Ti, Td, Tc])
        happycounter += 1
        print('happy', Perf, Kc, Ti, Td, Tc)

    data[counter] = np.array([Perf, Kc, Ti, Td, Tc])
    counter += 1

if happycounter == Nhappy:

```

```
break
```

```
from google.colab import files # this notebook was run with Colaboratory, which downloads files using
this library
np.savetxt("Data.csv", data, delimiter=",")
np.savetxt("HappyData.csv", happydata, delimiter=",")
files.download('HappyData.csv')

fasterplan(5688.814947611792, 0.0002280222206125743, 0.4941522520819933,
0.006245557968152839, s, times, Gd, Gp)
# happy 6.789263931270320 8157.95407778562 0.00014069840043239406 0.13349633544031736
0.0010902891735579206
# happy 6.769239197968654 6780.9431099381745 0.0008394599924216926 0.6232736552360005
0.01064341130569476
# happy 6.661657297636582 9535.386683958759 0.00010033885457162226 0.819218758695484
0.004582526747423241
# happy 6.604902873671916 8763.00366411034 0.00021935638604842907 0.17331925291467143
0.0034497938673252715
# happy 6.603490145150944 5688.814947611792 0.0002280222206125743 0.4941522520819933
0.006245557968152839
```