1. a.

For the given problem as we can see the first dataset is giving highest amount of prediction its 76.26% & the discrete-time poles are coming as 0.9990 & 0.9023. & the corresponding continuous time poles will be at -0.0010 & -0.1028.

So, clearly the system is showing multiscale nature & the first data set has rightly captured the nature of both the dynamics(slow & fast) which can be seen from the I/O plot of the first dataset as well.

Now, for the second data set is showing a first-order system with a discrete-time pole at 0.9097. which maps to a continuous time pole at s=-0.0956~-0.1 so the second dataset only captures the fast dynamics of the process which is evident for the second input.Due to this incompetence the second dataset yields a predictability of 57%.

Now, the third data set it only capture the slow dynamics of the process which a low frequency Sinusoidal input the discrete time pole corresponding to the system is coming as 0.9952 & the corresponding continuous time pole will be at -0.0048.

So, due to this It attains only 47% predictability.

1. b.

The first dataset is carrying more information about the poles(multiscale ) nature of the system. Clearly the predictions obtained from data1 is 76% which is still not sufficient. So, what I did was I used PEM estimators it gave optimal estimators & the residuals were white & cross-correlation of the input & the residuals obtained were almost negligible at all the lags & I got good amount of predictability for the first dataset but besides that one thing I thought of doing but I could not implement in due to time constraints that is as the system is multiscale in nature the effect of the second pole will retain for less amount of time compared to the pole responsible for slow dynamics

So, what I thought was from the impulse response estimate I will do a wavelet transform of it .Then from the wavelet transform I can get an idea of the multiscaled poles present in the system then after solving an Ordinary Least Square problem I can get the parameter values also.

Transfer functions

For data1

0.425(-\+0.00345) z^-1 - 0.48(-\+0.000596) z^-2 ----------------------------------------------------------------------------

1 - 1.902 (-\+0.1664)z^-1 + 0.9014(-\+0.5434) z^-2

For data2

0.48(-\+0.002589) z^-1

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1 - 0.95 (-\+0.0598)z^-1

For data3

0.0368(+\-0.00158) z^-1

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1 - 0.9955 (+\-0.00158)z^-1

Using Pem estimator

Data1

Discrete-time identified state-space model:

x(t+Ts) = A x(t) + B u(t) + K e(t)

y(t) = C x(t) + D u(t) + e(t)

A =

x1 x2

x1 0.9851 +/- 3.12e+09 0.0345 +/- 2.378e+09

x2 0.0334 +/- 7.446e+09 0.9163 +/- 3.12e+09

B =

u1

x1 0.001105 +/- 1.055e+08

x2 -0.002592 +/- 2.364e+08

C =

x1 x2

y1 277.7 +/- 3.554e+14 -68.92 +/- 1.534e+14

D =

u1

y1 0

K =

y1

x1 -3.314e-06 +/- 4.922e+05

x2 7.14e-06 +/- 7.005e+05

Transfer function

0.4855 z^-1 - 0.4845 z^-2

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1 - 1.901 z^-1 + 0.9014 z^-2

For 2nd dataset

Discrete-time identified state-space model:

x(t+Ts) = A x(t) + B u(t) + K e(t)

y(t) = C x(t) + D u(t) + e(t)

A =

x1

x1 0.9097 +/- 0.0009568

B =

u1

x1 0.001859 +/- 3.072e+10

C =

x1

y1 251.2 +/- 4.151e+15

D =

u1

y1 0

K =

y1

x1 0.000308 +/- 5.09e+09

The corresponding transfer function will be

0.467 z^-1

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1 - 0.9097 z^-1

For the 3rd dataset

fit2 =

Discrete-time identified state-space model:

x(t+Ts) = A x(t) + B u(t) + K e(t)

y(t) = C x(t) + D u(t) + e(t)

A =

x1

x1 0.9952 +/- 0.0003644

B =

u1

x1 0.0009268 +/- 6.697e+09

C =

x1

y1 39.39 +/- 2.846e+14

D =

u1

y1 0

K =

y1

x1 0.001282 +/- 9.267e+09

The corresponding discrete-time transfer function will be

0.0365 z^-1

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1 - 0.9952 z^-1