## Modelling Options for Networks with Delay: DDEs, DDFs, PDEs, and PIEs

Matthew Peet, S. Shivakumar, S. Wu, S. Weiland, A. Das, K. Gu et al. Arizona State University Tempe, AZ USA

## Coupled Communications and Autonomy Challenges in Connected Autonomous Vehicles NSF CPS PI Meeting 2019

November 21, 2019

## Control of a Network of Vehicles with Delay

Consider the dynamics of a swarm of UAVs:

$$
\begin{array}{rlrl}
\dot{x}_{i}(t) & =a_{i} x_{i}(t)+\sum_{j=1}^{N} a_{i j} x_{j}\left(t-\hat{\tau}_{i j}\right)+b_{1 i} w\left(t-\bar{\tau}_{i}\right)+b_{2 i} u\left(t-h_{i}\right) \\
z(t) & =C_{1} x(t)+D_{12} u(t) & \text { Regulated Output } \\
y_{i}(t) & =c_{2 i} x_{i}\left(t-\tilde{\tau}_{i}\right)+d_{21 i} w\left(t-\tilde{\tau}_{i}\right) & \text { Sensed output }
\end{array}
$$

Dynamics:

- $a_{i}$ is the internal dynamics of UAV $i$
- $a_{i j}$ is the effect of UAV $j$ on UAV $i$.
- $b_{1 i}$ is the effect of noise on UAV $i$
- $b_{2 i}$ is the effect of the controller on UAV $i$
- $c_{2 i}$ is the measured output of from UAV $i$
- $d_{21 i}$ is the effect of noise on the sensor on UAV $i$
- $C_{1}$ is the output of states to minimize in the optimal control problem
- $D_{12}$ is the actuator output to minimize in the optimal control problem

Delays:

- $\hat{\tau}_{i j}$ is the state delay from UAV $j$ to UAV $i$
- $h_{i}$ is the input delay from controller to reach UAV $i$
- $\bar{\tau}_{i}$ is the process delay (wind, tracking signal, et c.) for UAV $i$
- $\tilde{\tau}_{i}$ is the measurement delay from UAV $i$ to controller


## Optimal Control Form using Delay-Diff. Equations (DDEs)

General Form of Optimal Control Problem using DDEs:

$$
\begin{aligned}
& \dot{x}(t)=A_{0} x(t)+B_{1} w(t)+B_{2} u(t)+\sum_{i=1}^{N}\left(A_{i} x\left(t-\tau_{i}\right)+B_{1 i} w\left(t-\tau_{i}\right)+B_{2 i} u\left(t-\tau_{i}\right)\right) \\
& z(t)=C_{10} x(t)+D_{11} w(t)+D_{12} u(t)+\sum_{i=1}^{N}\left(C_{1 i} x\left(t-\tau_{i}\right)+D_{11 i} w\left(t-\tau_{i}\right)+D_{12 i} u\left(t-\tau_{i}\right)\right) \\
& y(t)=C_{20} x(t)+D_{21} w(t)+D_{22} u(t)+\sum_{i=1}^{N}\left(C_{2 i} x\left(t-\tau_{i}\right)+D_{21 i} w\left(t-\tau_{i}\right)+D_{22 i} u\left(t-\tau_{i}\right)\right)
\end{aligned}
$$

Equations: State Equation; Regulated Output; Sensed Output


Problem:

- No network Structure!

Problems:

- Utterly Intractable
- Can't represent some networks

For Simplicity, I leave off the distributed-delay terms. EVERYTHING is infinite-dimensional $-x$ and $w$ and $u$

## Estimators

2019-11-21
Optimal Control Form using Delay-Diff. Equations (DDEs)

Optimal Control Form using Delay-Diff. Equations (DDEs) General Form of Optimal Control Problem using DDEs:

$9(N+1)$ matrices needed to define system

## A Network as a DDE

Network Model (neglecting state delays):

$$
\begin{aligned}
\dot{x}_{i}(t) & =a_{i} x_{i}(t)+\sum_{j=1}^{N} a_{i j} x_{j}(t)+b_{1 i} w\left(t-\tau_{i}\right)+b_{2 i} u\left(t-\tau_{N+i}\right) \\
z(t) & =C_{1} x(t)+D_{12} u(t) \\
y_{i}(t) & =c_{2 i} x_{i}\left(t-\tau_{2 N+i}\right)+d_{21 i} w\left(t-\tau_{2 N+i}\right) .
\end{aligned}
$$

DDE Representation:

$$
\begin{aligned}
\dot{x}(t) & =A_{0} x(t)+\sum_{i=1}^{N} B_{1 i} w\left(t-\tau_{i}\right)+\sum_{j=N+1}^{2 N} B_{2 i} u\left(t-\tau_{i}\right) \\
z(t) & =C_{10} x(t)+D_{12} u(t) \\
y(t) & =\sum_{i=2 N+1}^{3 N} C_{2 i} x\left(t-\tau_{i}\right)+\sum_{i=2 N+1}^{3 N} D_{21 i} w\left(t-\tau_{i}\right)
\end{aligned}
$$

Problem: delayed information has dimension $3 N\left(n_{x} \cdot N+n_{w}+n_{u}\right)$ where here $N$ is \# of UAVs.

## Some Networks CANNOT be modelled using DDEs

Network model with input delay:

$$
\begin{aligned}
& \dot{x}(t)=A_{0} x(t)+B_{1} w(t)+\sum_{i=1}^{N} B_{2 i} u\left(t-\tau_{i}\right) \\
& z(t)=C_{1} x(t)+D_{12} u(t) \\
& y(t)=C_{2} x(t)+D_{21} w(t)+\sum_{i=1}^{N} D_{22 i} u\left(t-\tau_{i}\right)
\end{aligned}
$$

with STATIC FEEDBACK:

$$
u(t)=F y(t)
$$

Now, substituting $u(t)=F y(t)$ into the sensed output term, we obtain solutions of the form

$$
\begin{align*}
\dot{x}(t) & =A_{0} x(t)+B_{1} w(t)+\sum_{i} B_{2 i} F y\left(t-\tau_{i}\right) \\
z(t) & =C_{1} x(t)+D_{12} F y(t) \\
y(t) & =C_{2} x(t)+D_{21} w(t)+\sum_{i=1}^{N} D_{22 i} F y\left(t-\tau_{i}\right) . \tag{1}
\end{align*}
$$

There is no DDE which satisfies Eqns. (1) due to the recursion in the output.

## Advantages/Disadvantages of DDE formulation

## Advantages:

- Well studied
- State delay well-studied using LK functions
- Input delay handled by Smith predictors
- Padé approximations, LMI methods, SOS methods, etc.
- Always Well-Posed


## Disadvantages?

- Lots of delay terms everywhere
- Implies lots of information is delayed
- Can't represent some models
- Many tools implicitly treat as a PDE


## Optimal Control via Diff.-DiFFerence Equations (DDFs)

DDFs separate delayed information into low-dimensional channels

$$
\begin{aligned}
\dot{x}(t) & =A_{0} x(t)+B_{1} w(t)+B_{2} u(t)+B_{v} v(t) \\
z(t) & =C_{1} x(t)+D_{11} w(t)+D_{12} u(t)+D_{1 v} v(t) \\
y(t) & =C_{2} x(t)+D_{21} w(t)+D_{22} u(t)+D_{2 v} v(t) \\
r_{i}(t) & =C_{r i} x(t)+B_{r 1 i} w(t)+B_{r 2 i} u(t)+D_{r v i} v(t) \\
v(t) & =\sum_{i=1}^{N} C_{v i} r_{i}\left(t-\tau_{i}\right)+\sum_{i=1}^{N} \int_{-\tau_{i}}^{0} C_{v d i}(s) r_{i}(t+s) d s
\end{aligned}
$$

The information which is being delayed is stored in the information channels $r_{i}(t)$

- State in green is the infinite-dimensional part of the state
- Allows for lower-dimensional states
- Allows for simple difference equations (Discrete time) using $D_{r v i}$


## Converting a DDE to a DDF

## DDE Formulation:

$$
\begin{aligned}
& \dot{x}(t)=A_{0} x(t)+B_{1} w(t)+B_{2} u(t)+\sum_{i=1}^{N}\left(A_{i} x\left(t-\tau_{i}\right)+B_{1 i} w\left(t-\tau_{i}\right)+B_{2 i} u\left(t-\tau_{i}\right)\right) \\
& z(t)=C_{10} x(t)+D_{11} w(t)+D_{12} u(t)+\sum_{i=1}^{N}\left(C_{1 i} x\left(t-\tau_{i}\right)+D_{11 i} w\left(t-\tau_{i}\right)+D_{12 i} u\left(t-\tau_{i}\right)\right) \\
& y(t)=C_{20} x(t)+D_{21} w(t)+D_{22} u(t)+\sum_{i=1}^{N}\left(C_{2 i} x\left(t-\tau_{i}\right)+D_{21 i} w\left(t-\tau_{i}\right)+D_{22 i} u\left(t-\tau_{i}\right)\right)
\end{aligned}
$$

## DDF Formulation:

$$
\begin{aligned}
\dot{x}(t) & =A_{0} x(t)+B_{1} w(t)+B_{2} u(t)+B_{v} v(t) \\
z(t) & =C_{1} x(t)+D_{11} w(t)+D_{12} u(t)+D_{1 v} v(t) \\
y(t) & =C_{2} x(t)+D_{21} w(t)+D_{22} u(t)+D_{2 v} v(t) \\
r_{i}(t) & =C_{r i} x(t)+B_{r 1 i} w(t)+B_{r 2 i} u(t)+D_{r v i} v(t) \\
v(t) & =\sum_{i=1}^{N} C_{v i} r_{i}\left(t-\tau_{i}\right)+\sum_{i=1}^{N} \int_{-\tau_{i}}^{0} C_{v d i}(s) r_{i}(t+s) d s
\end{aligned}
$$

## Converting a DDE to a DDF

## DDF Formulation:

$$
\begin{aligned}
\dot{x}(t) & =A_{0} x(t)+B_{1} w(t)+B_{2} u(t)+B_{v} v(t) \\
z(t) & =C_{1} x(t)+D_{11} w(t)+D_{12} u(t)+D_{1 v} v(t) \\
y(t) & =C_{2} x(t)+D_{21} w(t)+D_{22} u(t)+D_{2 v} v(t) \\
r_{i}(t) & =C_{r i} x(t)+B_{r 1 i} w(t)+B_{r 2 i} u(t)+D_{r v i} v(t) \\
v(t) & =\sum_{i=1}^{K} C_{v i} r_{i}\left(t-\tau_{i}\right)+\sum_{i=1}^{K} \int_{-\tau_{i}}^{0} C_{v d i}(s) r_{i}(t+s) d s
\end{aligned}
$$

In order of appearance (all other matrices unchanged):

$$
\left.\begin{array}{rl}
B_{v}= & {\left[\begin{array}{lll}
I & 0 & 0
\end{array}\right], \quad D_{1 v}=\left[\begin{array}{lll}
0 & I & 0
\end{array}\right] \quad D_{2 v}=\left[\begin{array}{lll}
0 & 0 & I
\end{array}\right]} \\
C_{r i} & =\left[\begin{array}{l}
I \\
0 \\
0
\end{array}\right], \quad B_{r 1 i}=\left[\begin{array}{l}
0 \\
I \\
0
\end{array}\right], \quad B_{r 2 i}=\left[\begin{array}{l}
0 \\
0 \\
I
\end{array}\right], \quad D_{r v i}=0
\end{array}\right]=\left[\begin{array}{ccc}
A_{i} & B_{1 i} & B_{2 i} \\
C_{1 i} & D_{11 i} & D_{12 i} \\
C_{2 i} & D_{21 i} & D_{22 i}
\end{array}\right], \quad C_{v d i}(s)=\left[\begin{array}{ccc}
A_{d i}(s) & B_{1 d i}(s) & B_{2 d i}(s) \\
C_{1 d i}(s) & D_{11 d i}(s) & D_{12 d i}(s) \\
C_{2 d i}(s) & D_{21 d i}(s) & D_{22 d i}(s)
\end{array}\right] .
$$

## Reverse Transformation (DDF to DDE) Not Possible

## Standard Network Model using DDF Formulation

Network Model (neglecting state delays):

$$
\begin{aligned}
\dot{x}_{i}(t) & =a_{i} x_{i}(t)+\sum_{j=1}^{N} a_{i j} x_{j}(t)+b_{1 i} w\left(t-\tau_{i}\right)+b_{2 i} u\left(t-\tau_{N+i}\right) \\
z(t) & =C_{1} x(t)+D_{12} u(t) \\
y_{i}(t) & =c_{2 i} x_{i}\left(t-\tau_{2 N+i}\right)+d_{21 i} w\left(t-\tau_{2 N+i}\right)
\end{aligned}
$$

The DDF representation:

$$
\begin{array}{cc}
\dot{x}(t)=A_{0} x(t)+\sum_{i=1}^{2 N} v_{i}(t) \\
z(t)=C_{10} x(t)+D_{12} u(t) \\
y(t)=\left[\begin{array}{lll}
0 & 0 & I
\end{array}\right] v(t) \\
v(t)=\left[\begin{array}{c}
r_{1}\left(t-\tau_{1}\right) \\
\vdots \\
r_{3 N}\left(t-\tau_{3 N}\right)
\end{array}\right] & r_{i}(t)= \begin{cases}b_{1 i} w(t) & \\
b_{2, i-N} u(t) \\
c_{2, i-2 N} x_{i-2 N}(t)+d_{21, i-2 N} w(t) & \\
i \in[2 N+1, N]\end{cases}
\end{array}
$$

The state-space dimension of the delayed component is $\left(2 n_{x}+n_{y}\right) N$ (vs. $3 N\left(n_{x} N+n_{w}+n_{u}\right)$ for the DDE). $y_{i} \in \mathbb{R}^{n_{y}}, x_{i} \in \mathbb{R}^{n_{x}}$.

Estimators

Standard Network Model using DDF Formulation Network Model (neglecting state delays):
$\dot{x}_{i}(t)=a_{j} x_{d}(t)+\sum_{j=1}^{N} a_{c_{y}} x_{j}(t)+b_{1,} w\left(t-n_{3}\right)+b_{2} u_{j}\left(t-\tau_{N+i}\right)$ $z(t)=C_{1 x}(t)+D_{12 u} u(t)$
$y_{1}(t)=c_{31} x_{i}\left(t-\tau_{2 N+i}\right)+d_{21} w\left(t-\tau_{2 N+i}\right)$. The DDF representation:

Definition of $r$ was chosen assuming dimension of $x_{i}$ is less than that of $w$ or $u$. Otherwise choose

$$
r_{i}(t)= \begin{cases}w(t) & i \in[1, N] \\
u(t) & i \in[N+1,2 N] \\
{\left[\begin{array}{c}
x_{i-2 N}(t) \\
w(t)
\end{array}\right]} & i \in[2 N+1,3 N]\end{cases}
$$

or

$$
r_{i}(t)= \begin{cases}w(t) & i \in[1, N] \\ u(t) & i \in[N+1,2 N] \\ c_{2, i-2 N} x_{i-2 N}(t)+d_{21, i-2 N} w(t) & i \in[2 N+1,3 N]\end{cases}
$$

## A Network which is a DDF but not a DDE

Static State Feedback Model:

$$
\begin{aligned}
& \dot{x}(t)=A_{0} x(t)+B_{1} w(t)+\sum_{i} B_{2 i} F y\left(t-\tau_{i}\right) \\
& z(t)=C_{1} x(t)+D_{12} F y(t) \\
& y(t)=C_{2} x(t)+D_{21} w(t)+\sum_{i=1}^{N} D_{22 i} F y\left(t-\tau_{i}\right)
\end{aligned}
$$

DDF Representation:

$$
\begin{aligned}
\dot{x}(t) & =A_{0} x(t)+B_{1} w(t)+\sum_{i=1}^{N} B_{2 i} v_{i}(t) \\
z(t) & =\left(C_{1}+D_{12} F C_{2}\right) x(t)+D_{12} F D_{21} w(t)+D_{12} F D_{2 v} \sum_{i=1}^{N} D_{22 i} v_{i}(t) \\
y(t) & =C_{2} x(t)+D_{21} w(t)+\sum_{i=1}^{N} D_{22 i} v_{i}(t) \\
r_{i}(t) & =F C_{2} x(t)+F D_{21} w(t)+F D_{22 i} v_{i}(t) \\
v_{i}(t) & =r_{i}\left(t-\tau_{i}\right)
\end{aligned}
$$

## Advantages/Disadvantages of DDF formulation

## Advantages:

- Use of low dimensional channels
- Reduces computation complexity of all analysis and control algorithms
- Padé approximations, LMI methods, SOS methods, etc.
- Can represent difference equations


## Disadvantages:

- Relatively few analysis and controls techniques available
- Literature is Sparse
- Well-posedness is not assumed


## Optimal Control via ODE-PDE Formulation

Almost identical to DDF formulation

- Information channels are represented by PDEs of form $u_{t}=u_{s}$

$$
\begin{aligned}
\dot{x}(t) & =A_{0} x(t)+B_{1} w(t)+B_{2} u(t)+B_{v} v(t) \\
z(t) & =C_{1} x(t)+D_{11} w(t)+D_{12} u(t)+D_{1 v} v(t) \\
y(t) & =C_{2} x(t)+D_{21} w(t)+D_{22} u(t)+D_{2 v} v(t) \\
\dot{\phi}_{i}(t, s) & =\frac{1}{\tau_{i}} \phi_{i, s}(t, s) \quad \phi_{i}(t, 0)=C_{r i} x(t)+B_{r 1 i} w(t)+B_{r 2 i} u(t)+D_{r v i} v(t) \\
v(t) & =\sum_{i=1}^{N} C_{v i} \phi_{i}(t,-1)+\sum_{i=1}^{N} \int_{-1}^{0} \tau_{i} C_{v d i}\left(\tau_{i} s\right) \phi_{i}(t, s) d s
\end{aligned}
$$

An extension of the DDF formulation

- $\phi_{i}(t)$ is same as $r_{i}(t)$ was in the DDF
- PDE state is in green.
- Coupled to ODE through Boundary Conditions.


## Advantages/Disadvantages of ODE-PDE formulation

Class of Systems Considered: Includes the DDF class of systems

## Advantages:

- Use of low dimensional channels
- Tools developed for PDEs can be applied
- Discretization schemes
- Backstepping methods for control
- More physical interpretation?


## Disadvantages:

- Use of unbounded operators
- Dirac operators
- Differential operators


## The Partial-Integral Equation (PIE) Formulation

$$
\begin{align*}
\mathcal{T} \dot{\mathrm{x}}(t)+\mathcal{B}_{T_{1}} \dot{w}(t)+\mathcal{B}_{T_{2}} \dot{u}(t) & =\mathcal{A} \mathbf{x}(t)+\mathcal{B}_{1} w(t)+\mathcal{B}_{2} u(t) \\
z(t) & =\mathcal{C}_{1} \mathbf{x}(t)+\mathcal{D}_{11} w(t)+\mathcal{D}_{12} u(t) \\
y(t) & =\mathcal{C}_{2} \mathbf{x}(t)+\mathcal{D}_{21} w(t)+\mathcal{D}_{22} u(t) \tag{2}
\end{align*}
$$

where $\mathcal{T}, \mathcal{A}, \mathcal{B}_{i}, \mathcal{C}_{i}, \mathcal{D}_{i j}$ are Partial Integral (4-PI) operators of the form

$$
(\mathcal{P}\left\{\begin{array}{c}
P, Q_{1} \\
Q_{2},\left\{R_{i}\right\}
\end{array}\right\} \underbrace{\left[\begin{array}{c}
x \\
\Phi
\end{array}\right]}_{\mathrm{x}})(s):=\left[\begin{array}{c}
P x+\int_{-1}^{0} Q_{1}(s) \Phi(s) d s \\
Q_{2}(s) x+\left(\mathcal{P}_{\left\{R_{i}\right\}} \Phi\right)(s)
\end{array}\right]
$$

where $\mathcal{P}_{\left\{R_{i}\right\}}$ is a 3-PI operator of the form:

$$
\left(\mathcal{P}_{\left\{R_{i}\right\}} \Phi\right)(s):=R_{0}(s) \Phi(s)+\int_{-1}^{s} R_{1}(s, \theta) \Phi(\theta) d \theta+\int_{s}^{0} R_{2}(s, \theta) \Phi(\theta) d \theta
$$

The state is in $\mathbb{R}^{n_{1}} \times \mathbb{R}^{n_{2}}$

- Dimensions are the same as the ODE-PDE framework
- 4-PI operators are bounded, algebraic.
- Can be used as matrices in LMIs (yielding LOIs)


## Linear Operator Inequalities (LOIs) in the PIE Formulation

## PIE formulation of System:

All results on this page are for no input delays $\left(B_{T 1}=0\right)$ and no process delays $\left(B_{T 2}=0\right)$

- Extension OK to input delays.

$$
\begin{aligned}
\mathcal{T} \dot{\mathrm{x}}(t) & =\mathcal{A} \mathrm{x}(t)+\mathcal{B}_{1} w(t)+\mathcal{B}_{2} u(t) \\
z(t) & =\mathcal{C}_{1} \mathrm{x}(t)+\mathcal{D}_{11} w(t)+\mathcal{D}_{12} u(t) \\
y(t) & =\mathcal{C}_{2} \mathrm{x}(t)+\mathcal{D}_{21} w(t)+\mathcal{D}_{22} u(t)
\end{aligned}
$$

## KYP and $H_{\infty}$-Gain

If there exists $\mathcal{P}=\mathcal{P}\left\{\begin{array}{c}P, \\ Q_{2},\left\{R_{1}\right. \\ R_{i}\end{array}\right\} \geq 0$ such that

$$
\left[\begin{array}{ccc}
-\gamma I & \mathcal{D}_{11}^{*} & \mathcal{B}_{1}^{*} \mathcal{P} \mathcal{T} \\
\mathcal{D}_{1} & -\gamma I & \mathcal{C}_{1} \\
\mathcal{T}^{*} \mathcal{P} \mathcal{B}_{1} & \mathcal{C}_{1}^{*} & \mathcal{A}^{*} \mathcal{P} \mathcal{T}+\mathcal{T}^{*} \mathcal{P A}
\end{array}\right]<0
$$

then $\|z\|_{L_{2}} \leq \gamma\|\omega\|_{L_{2}}$.

## $H_{\infty}$-Optimal Full State Feedback: $H_{\infty}$-Optimal Estimator Design:

If there exist $\mathcal{P}=\mathcal{P}\left\{\begin{array}{c}P, Q^{P} \\ Q^{T},\left\{R_{i}\right\}\end{array}\right\}>0$ and $\mathcal{Z}=\mathcal{P}\left\{\begin{array}{l}z_{1}, z_{2} \\ \varnothing,\{\phi\}\end{array}\right\}$ such that
 then if $u(t)=\mathcal{Z P}^{-1} \mathbf{x}(t),\|z\|_{L_{2}} \leq \gamma\|\omega\|_{L_{2}}$.

If there exist $\mathcal{P}=\mathcal{P}\left\{\begin{array}{c}P, \\ Q^{T},\left\{R_{i}\right\}\end{array}\right\} \geq 0$ and $\mathcal{Z}=\mathcal{P}\left\{\begin{array}{c}z_{1}, \emptyset \\ z_{2},\{\emptyset\}\end{array}\right\}$ such that then if $\mathcal{L}=\mathcal{P}^{-1} \mathcal{Z},\|\hat{z}-z\|_{L_{2}} \leq \gamma\|\omega\|_{L_{2}}$ where

$$
\begin{aligned}
\mathcal{T} \dot{\hat{\mathbf{x}}}(t) & =\mathcal{A} \hat{\mathbf{x}}(t)+\mathcal{L}(\hat{y}(t)-y(t)) \\
\hat{y}(t) & =\mathcal{C}_{2} \hat{\mathbf{x}}(t) \quad \hat{z}(t)=\mathcal{C}_{1} \hat{\mathbf{x}}(t)
\end{aligned}
$$

## PIETOOLS Code for solving Linear Operator Inequalities

## PIE formulation of System:

```
pvar s,th,gam;
T = sosprogram([s,th],gam);
opvar A,B1,B2,C1,C2,D11,D12,D21,E;
A= . ; B1 = . ; B2= . ; C1= . ; C2= . ;
D11=. .;D12=. .;D21=. .;E=..;
```


## KYP and $H_{\infty}$-Gain

```
[T,P] = sos_posopvar(T,dim,I,s,th);
D = [-gam*I D11, B1'*P*E;
D11 -gam*I C1;
E'*P*B1 C1' A'*P*E+E'*P*A];
T = sosopineq(T,D);
T = sossetobj(T,gam);
```


## $H_{\infty}$-Optimal Full State Feedback: $H_{\infty}$-Optimal Estimator Design:

```
[T,P] = sos_posopvar(T,dim,I,s,th,deg); [T,P] = sos_posopvar(T,dim,I,s,th);
```

$[T, P]=$ sos_opvar (T, dim, $I, s$, th, deg) ;
$\mathrm{M} 33=(\mathrm{A} * \mathrm{P}+\mathrm{B} 2 * \mathrm{Z}) * \mathrm{E}^{\prime}+\mathrm{E} *(\mathrm{~A} * \mathrm{P}+\mathrm{B} 2 * \mathrm{Z})^{\prime}$
$[T, P]=$ sos_opvar (T,dim,I,s,th,deg);
M33 $=(P * A+Z * C 2)^{\prime} * E+E{ }^{\prime} *(P * A+Z * C 2)$
$\mathrm{M} 13=(\mathrm{C} 1 * \mathrm{P}+\mathrm{D} 12 * \mathrm{Z}) * \mathrm{E}^{\prime}$
$\mathrm{M} 13=-\mathrm{B} 1^{\prime} * \mathrm{P} * \mathrm{E}-\mathrm{D} 21^{\prime} * \mathrm{Z}^{\prime} * \mathrm{E}$
D $=[-\operatorname{gam} * I \quad$ D11, M13;
D11 -gam*I B1';
M13 B1 M33] ;

```
T = sosopineq(T,D);
T = sossetobj(T,gam);
T = sossolve(T);
T = sosopineq(T,D);
T = sossetobj(T,gam);
T = sossolve(T);
```

D $=[-\operatorname{gam} * I \quad$ D11, M13;
D11 -gam*I C1;
M13, C1, M33];

## Advantages/Disadvantages of PIE formulation

Class of Systems Considered: Includes the DDF class of systems

## Advantages:

- Actually Old (Barbasin type)
- Use of low dimensional channels
- Tools developed for ODEs can be applied
- LMIs
- Manipulation is easy


## Disadvantages:

- Not many results in this area
- Relatively New
- Literature is Sparse
- Similar Structure to Singular Systems


## A network control problem in the DDE formulation

$$
\begin{aligned}
& \dot{x}(t)=A_{0} x(t)+\sum_{i} A_{i} x\left(t-\tau_{i}\right)+B_{1} w(t)+B_{2} u(t), \quad y(t)=C x(t)+D_{1} w(t)+D_{2} u(t) \\
& \text { where }
\end{aligned}
$$

$$
\left.\left.\begin{array}{rl}
A_{0} & =\left[\begin{array}{ll}
0 & I \\
0 & 0
\end{array}\right], \quad A_{i}=\left[\begin{array}{cc}
0 & 0 \\
0 & \hat{A}_{i}
\end{array}\right], \quad B_{1}=\left[\begin{array}{c}
-I \\
-\hat{\Gamma}+\operatorname{diag}\left(\alpha_{1} \ldots \alpha_{K}\right)
\end{array}\right] \\
\hat{A}_{i}(:, i) & =\alpha_{i}\left[\begin{array}{llll}
\gamma_{i, 1} & \ldots & \gamma_{i, i-1} & -1
\end{array} \gamma_{i, i-1}\right. \\
\ldots & \gamma_{i, K}
\end{array}\right]^{T}\right]\left(\begin{array}{lll}
\hat{\Gamma}_{i j} & =\alpha_{j} \gamma_{i j}=\left[\begin{array}{lll}
q_{1} & \ldots & q_{K}
\end{array}\right], \quad B_{2}=\left[\begin{array}{l}
0 \\
I
\end{array}\right] \\
C_{0} & =\left[\begin{array}{ll}
I & 0 \\
0 & 0
\end{array}\right], \quad C_{1}=\left[\begin{array}{ll}
0 & 0 \\
0 & 0
\end{array}\right], \quad D_{1}=\left[\begin{array}{l}
0 \\
0
\end{array}\right], \quad D_{2}=\left[\begin{array}{c}
0 \\
.1 I
\end{array}\right]
\end{array}\right.
$$



Complexity: 8 states, 4 delays, 4 inputs, 4 disturbances, 8 regulated outputs
Results: A Matlab simulation of the step response of the closed-loop dynamics $\left(T_{2 i}(t)\right.$ ) with 4 users ( $w_{i}$ and $\tau_{i}$ as indicated) coupled with the controller with closed-loop gain of .48

## Converting a DDF to a PIE

## DDF Formulation:

$$
\begin{aligned}
\dot{x}(t) & =A_{0} x(t)+B_{1} w(t)+B_{2} u(t)+B_{v} v(t) \\
z(t) & =C_{1} x(t)+D_{11} w(t)+D_{12} u(t)+D_{1 v} v(t) \\
y(t) & =C_{2} x(t)+D_{21} w(t)+D_{22} u(t)+D_{2 v} v(t) \\
r_{i}(t) & =C_{r i} x(t)+B_{r 1 i} w(t)+B_{r 2 i} u(t)+D_{r v i} v(t) \\
v(t) & =\sum_{i=1}^{K} C_{v i} r_{i}\left(t-\tau_{i}\right)+\sum_{i=1}^{K} \int_{-\tau_{i}}^{0} C_{v d i}(s) r_{i}(t+s) d s
\end{aligned}
$$

## PIE Formulation:

$$
\begin{gather*}
\mathcal{T} \dot{\mathrm{x}}(t)+\mathcal{B}_{T_{1}} \dot{w}(t)+\mathcal{B}_{T_{2}} \dot{u}(t)=\mathcal{A} \mathrm{x}(t)+\mathcal{B}_{1} w(t)+\mathcal{B}_{2} u(t) \\
z(t)=\mathcal{C}_{1} \mathrm{x}(t)+\mathcal{D}_{11} w(t)+\mathcal{D}_{12} u(t), \\
y(t)=\mathcal{C}_{2} \mathrm{x}(t)+\mathcal{D}_{21} w(t)+\mathcal{D}_{22} u(t), \tag{3}
\end{gather*}
$$

## Converting a DDF to a PIE

$$
\mathbf{D}_{11}=\left(D_{11}+D_{1 v} D_{v w}\right), \mathbf{D}_{12}=\left(D_{12}+D_{1 v} D_{v u}\right), \mathbf{D}_{21}=\left(D_{21}+D_{2 v} D_{v w}\right), \mathbf{D}_{22}=\left(D_{22}+D_{2 v} D_{v u}\right)
$$

$$
\hat{C}_{v i}=C_{v i}+\int_{-1}^{0} \tau_{i} C_{v d i}\left(\tau_{i} s\right) d s, \quad D_{I}=\left(I-\left(\sum_{i=1}^{K} \hat{C}_{v i} D_{r v i}\right)\right)^{-1}, \quad C_{v x}=D_{I}\left(\sum_{i=1}^{K} \hat{C}_{v i} C_{r i}\right)
$$

$$
D_{v w}=D_{I}\left(\sum_{i=1}^{K} \hat{C}_{v i} B_{r 1 i}\right), D_{v u}=D_{I}\left(\sum_{i=1}^{K} \hat{C}_{v i} B_{r 2 i}\right), C_{I i}(s)=-D_{I}\left(C_{v i}+\tau_{i} \int_{-1}^{s} C_{v d i}\left(\tau_{i} \eta\right) d \eta\right)
$$

$$
\begin{aligned}
& \mathcal{A}:=\mathcal{P}\left\{\begin{array}{c}
\substack{\mathbf{A}_{0}, \mathbf{A} \\
0,\left\{I_{\tau}, 0,0\right\}}
\end{array}\right\}, \quad \mathcal{T}:=\mathcal{P}\left\{\begin{array}{l}
I, 0 \\
\mathbf{T}_{0},\left\{0, \mathbf{T}_{a}, \mathbf{T}_{b}\right\}
\end{array}\right\}
\end{aligned}
$$

$$
\begin{aligned}
& \mathbf{A}_{0}=A_{0}+B_{v} C_{v x}, \mathbf{A}(s)=B_{v}\left[C_{I 1}(s) \cdots C_{I K}(s)\right], \mathbf{B}_{1}=B_{1}+B_{v} D_{v w}, \mathbf{B}_{2}=B_{2}+B_{v} D_{v u} \\
& \mathbf{C}_{10}=C_{1}+D_{1 v} C_{v x}, \quad \mathbf{C}_{11}=D_{1 v}\left[\begin{array}{lll}
C_{I 1}(s) & \cdots & \left.C_{I K}(s)\right],
\end{array}\right. \\
& \mathbf{C}_{20}=C_{2}+D_{2 v} C_{v x}, \quad \mathbf{C}_{21}=D_{2 v}\left[\begin{array}{lll}
C_{I 1}(s) & \cdots & \left.C_{I K}(s)\right],
\end{array}\right.
\end{aligned}
$$

## Conclusion: What is the best way to represent a network?

The Last Slide (Thanks to NSF CNS-1739990)
Depends on your goal

- Control? Exploration? Consensus?


## DDEs:

- Convenient for small or delay-free networks
- Can use Padé approximation
- Smith Predictors, SOS
- Lots of literature
- No Difference equations


## ODE-PDEs:

- All the advantages of DDFs
- Good for intuition
- Good if you know how to use backstepping


## DDFs:

- Can use Padé approximation
- Not much literature
- Can be used for large networks and lots of delays
- Can combine discrete/continuous time
- OK for static feedback


## PIEs:

- Can use intuition from ODEs
- Can use PIETOOLS
- good for optimal control
- MAY be good for simulation (no BC's)
- Can apply PDE discretization schemes


## More Options?

## Illustration of $H_{\infty}$ Gain Analysis

## Example 1:

$$
\dot{x}(t)=\left[\begin{array}{cc}
-2 & 0 \\
0 & -.9
\end{array}\right] x(t)+\left[\begin{array}{cc}
-1 & 0 \\
-1 & -1
\end{array}\right] x(t-\tau)+\left[\begin{array}{c}
-.5 \\
1
\end{array}\right] w(t), \quad y(t)=\left[\begin{array}{ll}
1 & 0
\end{array}\right] x(t)
$$

| $d$ | 1 | 2 | 3 | Padé | [Fridman 2001] | [Shaked 1998] |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| $\gamma_{\min }$ | .2373 | .2365 | .2365 | .2364 | .32 | 2 |

Example 2: Stable for $\tau \in[.100173,1.71785]$ :
$\dot{x}(t)=\left[\begin{array}{cc}0 & 1 \\ -2 & .1\end{array}\right] x(t)+\left[\begin{array}{ll}0 & 0 \\ 1 & 0\end{array}\right] x(t-\tau)+\left[\begin{array}{ll}1 & 0 \\ 0 & 1\end{array}\right] w(t)$
$y(t)=\left[\begin{array}{ll}0 & 1\end{array}\right] x(t)$
We plot bounds for the $H_{\infty}$ norm as the delay varies within this interval. As expected, the $H_{\infty}$ norm approaches infinity quickly as we approach the limits of the stable region.


Figure: Calculated $H_{\infty}$ norm bound vs. delay for Ex. 2

## The Inverse of a 4-PI Operator is a 4-PI Operator!

Result from Keqin Gu
How to find (Note $R_{1}=R_{2}$ )

$$
\mathcal{K}=\mathcal{P}\left\{\begin{array}{c}
z_{1}, Z_{2} \\
\emptyset,\{\emptyset\}
\end{array}\right\} \mathcal{P}\left\{\begin{array}{c}
P, Q \\
Q^{T},\{S, R, R\}
\end{array}\right\}^{-1} ?
$$

Assume $Q$ and $R$ are polynomial

Extract Polynomial Coefficients: $Q(s)=H Z(s)$ and $R(s, \theta)=Z(s)^{T} \Gamma Z(\theta)$. Then $\mathcal{P}\left\{\begin{array}{c}P, Q \\ Q^{T},\{S, R, R\}\end{array}\right\}^{-1}=\mathcal{P}\left\{\underset{Q^{T},\left\{\begin{array}{l}\hat{S}, \hat{S}, \hat{R}, \hat{R}\}\end{array}\right\}}{\substack{\hat{S} \\ \hline}}\right.$ where

$$
\begin{aligned}
\hat{P} & =\left(I-\hat{H} V H^{T}\right) P^{-1}, & \hat{Q}(s)=\frac{1}{\tau} \hat{H} Z(s) S(s)^{-1} \\
\hat{S}(s) & =\frac{1}{\tau^{2}} S(s)^{-1} & \hat{R}(s, \theta)=\frac{1}{\tau} S(s)^{-1} Z(s)^{T} \hat{\Gamma} Z(\theta) S(\theta)^{-1},
\end{aligned}
$$

where

$$
\begin{aligned}
\hat{H} & =P^{-1} H\left(V H^{T} P^{-1} H-I-V \Gamma\right)^{-1} \\
\hat{\Gamma} & =-\left(\hat{H}^{T} H+\Gamma\right)(I+V \Gamma)^{-1}, \\
V & =\int_{-\tau}^{0} Z(s) S(s)^{-1} Z(s)^{T} d s
\end{aligned}
$$

## Boring Numerical Controller Synthesis Examples

$$
\begin{aligned}
\dot{x}(t) & =\left[\begin{array}{ll}
0 & 0 \\
0 & 1
\end{array}\right] x(t)+\left[\begin{array}{cc}
-1 & -1 \\
0 & -.9
\end{array}\right] x(t-\tau)+\left[\begin{array}{l}
1 \\
1
\end{array}\right] w(t)+\left[\begin{array}{l}
0 \\
1
\end{array}\right] u(t) \\
y(t) & =\left[\begin{array}{ll}
0 & 1 \\
0 & 0
\end{array}\right] x(t)+\left[\begin{array}{l}
0 \\
.1
\end{array}\right] u(t)
\end{aligned}
$$

| $d$ | 1 | 2 | 3 | Padé | Fridman 2003 | Li 1997 |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| $\gamma_{\min }(\tau=.999)$ | .10001 | .10001 | .10001 | .1000 | .22844 | 1.8822 |
| $\gamma_{\min }(\tau=2)$ | 1.43 | 1.36 | 1.341 | 1.340 | $\infty$ | $\infty$ |
| CPU sec | .478 | .879 | 2.48 | 2.78 | $\mathrm{~N} / \mathrm{A}$ | $\mathrm{N} / \mathrm{A}$ |

$$
\begin{array}{rl}
\dot{x}(t)= & {\left[\begin{array}{cc}
2 & 1 \\
0 & -1
\end{array}\right] x(t)+\left[\begin{array}{ll}
-1 & 0 \\
-1 & 1
\end{array}\right] x(t-\tau)+\left[\begin{array}{c}
-.5 \\
1
\end{array}\right] w(t)+\left[\begin{array}{l}
3 \\
1
\end{array}\right] u(t)} \\
y(t)= & {\left[\begin{array}{cc}
1 & -.5 \\
0 & 0
\end{array}\right] x(t)+\left[\begin{array}{l}
0 \\
1
\end{array}\right] u(t)} \\
& \frac{d}{\gamma_{\min }(\tau=.3)} \\
\hline \text { CPU sec } & .3953 \\
.655 & 1.248 \\
\hline
\end{array}
$$

## Easy Implementation, Optimal Results




| $\gamma_{\text {min }}$ | Example 1 |  |  | Example 2 |  |  | Example 3 |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  | $\mathrm{d}=1$ | $\mathrm{~d}=2$ | $\mathrm{~d}=4$ | $\mathrm{~d}=1$ | $\mathrm{~d}=2$ | $\mathrm{~d}=4$ | $\mathrm{~d}=1$ | $\mathrm{~d}=2$ |
| $\mathrm{~d}=4$ |  |  |  |  |  |  |  |  |
| using simplified estimator | 0.2371 | 0.23651 | 0.23608 |  | 7.2111 | 0.2264 |  |  |
| using generalized estimator | 0.2357 |  |  | 7.2111 | 0.2264 |  |  |  |
| Padé | 0.2357 |  |  | 7.2107 | 0.2264 |  |  |  |



## Systems with Input Delays (Control at the Boundary)

- When there is only one input delay, we may alternatively design an estimator using a delayed output (which then becomes a predictor) and is stable in closed-loop using the separation principle
- Control at the boundary is slightly more complex than in-domain control.

$$
\mathbf{x}_{p}=\mathcal{T} \mathbf{x}_{f}+\mathcal{B}_{T 2} u(t) \quad u(t)=\mathcal{K} \mathbf{x}_{f}(t)
$$

Replace $\mathcal{T} \rightarrow \mathcal{T}+\mathcal{B}_{T 2} \mathcal{K}$

$$
\left[\begin{array}{ccc}
-\gamma I & \mathcal{D}_{1} & \left(\mathcal{C P}+\mathcal{D}_{2} \mathcal{Z}\right)\left(\mathcal{T}+\mathcal{B}_{T 2} \mathcal{K}\right)^{*} \\
\mathcal{D}_{1}^{T} & -\gamma I & \mathcal{B}_{1}^{*} \\
\left(\mathcal{T}+\mathcal{B}_{T 2} \mathcal{K}\right)\left(\mathcal{C} \mathcal{P}+\mathcal{D}_{2} \mathcal{Z}\right)^{*} & \mathcal{B}_{1} & \left(\mathcal{A P}+\mathcal{B}_{2} \mathcal{Z}\right)\left(\mathcal{T}+\mathcal{B}_{T 2} \mathcal{K}\right)^{*}+\left(\mathcal{T}+\mathcal{B}_{T 2} \mathcal{K}\right)\left(\mathcal{A P}+\mathcal{B}_{2} \mathcal{Z}\right)^{*}
\end{array}\right]<\mathfrak{c}
$$

